Attribution of the Risk of Extreme Flood Events to Climate Change in the Context of Changing Land Use and Cover:

Case Study of The Shire River Basin Flood of 2015

by

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Date: 29th June 2018

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Dedicated to my mother and supportive family, and all the people putting an effort to protect Mother Earth!

Abstract

The 2015 flood event in the Shire River basin was characterised by Malawi Government's Department of Disaster Management (DoDMA) as the worst on record. It led to the damage in property worth millions of dollars with recovery still ongoing 3 years later. Over 150 fatalities were confirmed at the time with hundreds of others missing. The extent of the damage of the disaster was perhaps underlined by the swift adoption of the disaster management policy which was still in draft format then and the adoption of the climate change management policy a year later. In the aftermath of the disaster, as with most extreme weather events elsewhere around the world, questions were asked as to whether climate change might have had a hand in the occurrence of such an event and whether, going into a warmer climate, events of that nature of extremity will be the new normal.

By using the risk-based event attribution methodology based on dedicated attribution experiments with a global climate model, and focusing on one of the sub-catchments of the Shire River basin, this study explored whether climate change from anthropogenic sources might have influenced the likelihood of such an event occurring. However, given the nature of hydrological events and the land use history of the basin, land use and cover change is another potential flood risk factor which, if overlooked, might affect conclusions with regards to the contribution of external factors to the risk of flooding. To account for both climate change and land use and land change, four sets of rainfall-runoff simulations were run using the Hydrologiska Byrans Vattenbalans-avdelning (HBV) hydrological model which has the ability to simulate the impact of land use and climate change on rainfall-runoff relationships. Each set was a combination of a climate scenario-either "factual" or "counter-factual"-and land use and cover change scenario-either factual (historical) or counterfactual (current). The climate scenarios were based on simulated rainfall and temperature from the HadAM3p model run in two modes-the "factual" and "counter-factual"- simulating the climate with atmospheric conditions closely resembling the atmosphere at the time of occurrence of the event and the climate as it would have been without human emissions of greenhouse gases. The proportion of the risk was calculated to determine how the risk of experiencing a flood of the January-April 2015 magnitude (for 1-day, 10-day, and 30-day maximum flows) changes with climate change only, land use and cover change only, as well as both climate change and land use and cover change.

The results demonstrated that the probability of exceeding the 1-day maximum flow of the 2015 magnitude was lower in the factual (current) climate than in the counter-factual. However, changes in land use modify the flood risk such that, when land use change was accounted for, the extent of the reduction in the risk was lower. On the other hand, exceedance probabilities for 10-day and 30-day maximum flows were higher in the factual (current) climate. This was further heightened by changes in land use and cover. The study also established that observational uncertainties typical of the region may influence event attribution results to some extent. The results, which are based on a single attribution method and a single global climate model, do not span the method-model uncertainty range. As a consequence, the results are limited and do not constitute a fully defensible attribution statement.

Key Words (Phrases/Terms): Climate Change, Land Use and Cover Change, Extreme Event, Flood Risk, Factual, Counter-Factual, Attribution, Risk based approach (Probabilistic Event Attribution), Exceedance Probability, Fraction of Attributable Risk (FAR).

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List of Acronyms and Abbreviations

CHIRPS	Climate Hazard Infrared Precipitation with Stations
CMIP	Coupled Model Intercomparison Project
CSAG	Climate Systems Analysis Group
DCCMS	Department of Climate Change and Meteorological Services
DoDMA	Department of Disaster Management
ECDF	Empirical Cumulative Distribution Function
ESA	European Space Association
FAO	Food and Agriculture Organisation
FAR	Fraction of Attributable Risk
FCFA	Future Climate for Africa
GCM	Global Climate Model
GDP	Gross Domestic Product
GEV	Generalised Extreme Value
HBV	Hydrologiska Byrans Vattenbalans-avdelning
IHMS	Integrated Hydrological Modelling System
IPCC	Intergovernmental Panel on Climate Change
IPCC-SREX	Intergovernmental Panel on Climate Change's Special Report on Extreme Events
ISMIP	Inter-Sector Impact Model Inter-comparison Project
ITCZ	Inter-Tropical Convergence Zone
MCC	Meso-Scale Convective Complexes
JFM	January February March
LDEs	Long Duration Extreme Events
MVAC	Malawi Vulnerability Assessment Committee
OND	October November December
RCP	Representative Concentration Pathways
SADC	Southern African Development Community
SDEs	Short Duration Extreme
SOM	Self-Organising Map
SST	Sea Surface Temperature
SWAT	Soil and Water Assessment Tool
UMFULA	Uncertainty Reduction in Models for Understanding Development Applications

1 Introduction

1.1 Climate Change from Recent Assessments

There is overwhelming evidence suggesting anthropogenic interferences with the climate system and the recent Intergovernmental Panel on Climate Change (IPCC) concretise such evidence (Intergovernmental Panel on Climate Change [IPCC], 2013; 2018). From a plethora of studies with best available climate science and state of the art modelling, there is almost universally robust evidence that recent increases in global temperatures are as a result of emissions into the atmosphere of greenhouse gases, the bulk of which are from burning of fossil fuels. Projections of future climate indicate that this increase in global average temperatures will continue as a result of increasing concentration of greenhouse gases in the atmosphere. These changes in the greenhouse gas composition of the atmosphere, and the subsequent warming, will influence a number of weather and climate processes affecting not only temperature but other climate variables such as precipitation. The changes in the trends of such variables have been widely studied and, through detection and attribution studies, the influence of anthropogenic greenhouse gas emissions well documented.

Even though different for different climate variables, the robustness of such findings continues to improve as the understanding of the climate system (and how best it can be represented in climate models) improves, coupled with increasing years of observation during a time of increasing signal. Equally important is the improvement in computing capacity which makes it feasible to run climate models at fine resolution within a relatively short period of time. While the analysis of trends in climate variables dominates most climate change analyses, emphasis on particular events is a growing frontier in climate science, and a very important one given the societal connection that extreme events have as compared to trends. Despite that growing attention on events, understanding weather extremes and the extent to which they can be attributed to anthropogenic emissions poses one of the grand challenges which climate scientists face. Over time, however, the understanding of such extremes and methodologies of attributing them to climate change is improving, creating not only an opportunity for scientific endeavours, but a possibility for generation of climate information that may be useful in other spaces.

1.2 Attributing Extreme Weather Events to Anthropogenic Climate Change

It is so often the case that extreme weather events live long in the memory and years with extreme events are often used as reference years, or such events as reference events, in most natural sciences including climate science and hydrology. The damage that such events cause underlines the extent of their relevance to society (Hegerl, 2015). Such events are often debate and hypothesis-triggering such that, in their wake, questions are usually asked about what might have caused them. In the context of a changing climate, questions are often asked whether such events are as a result of climate change and whether events of such nature are going to be more frequent, or more severe going into a warmer climate(National Academies of Science Engineering and Medicine, 2016; Trenberth, Fasullo, & Shepherd, 2015). Questions about attributing extreme weather events are not the easiest to answer and, until the early 2000s, there was no widely recognised means of understanding how climate change might have had a hand in the occurrence of particular events (Otto, 2017). For events that have occurred, it is also particularly difficult to predict whether such events will occur again in the future and when. For all that is known, such events may still naturally occur without climate change given the natural variability typical of the climate system. However, a risk-based approach (Allen, 2003) is often used to determine the fraction of the risk or the likelihood of the event attributable to climate change. Event attribution questions and the need to address them is beyond academic realms as, from an operational point of view, science on extreme events helps inform better adaptation planning and proper disaster risk reduction and management. Such science would also be crucial in informing decisions about insurance and compensations for climate change related losses and damages.

1.3 Flood Risk and 2015 Floods in the Shire River Basin

This study was done for the Shire River basin in Malawi and particularly focused on the extreme flood event that occurred in January 2015. Flooding in the Shire River basin has intensified in recent years and may increase in both magnitude and frequency going into a warmer climate. Due to the geomorphology of the catchment, the Lower Shire Valley is the most affected and usually experiences the worse impacts when the river basin floods. Settlements and economic activities situated along flood plains in the valley are the most exposed and so often the most vulnerable. The increase in frequency and intensity of floods in the basin and elsewhere within the country has been chiefly attributed to climate change (Government of Malawi [GoM] in Malawi Hazards and Vulnerability Atlas, 2016). Observations between 1996 and 2015, illustrated in figure 1.1, highlight the increasing frequency of 5-year floods and the magnitude of the extreme event (50-year) of 2015. The increasing frequency of 5-year flood also reflects what is reported from studies under the Shire River Basin Management Programme, a government programme aimed at rehabilitating the river basin. The flood risk management component of the programme reports that 4-year floods have become more frequent, becoming almost annual and causing severe damage, more so in the Lower Shire Valley. It is also reported that siltation and raising of river beds accounts for the growing risk of flooding in the basin. Consequently, the urgency in flood mitigation has increased in order to reduce the exposure of the basin, including people and economic activities within the basin, to climatic extremes, specifically floods.

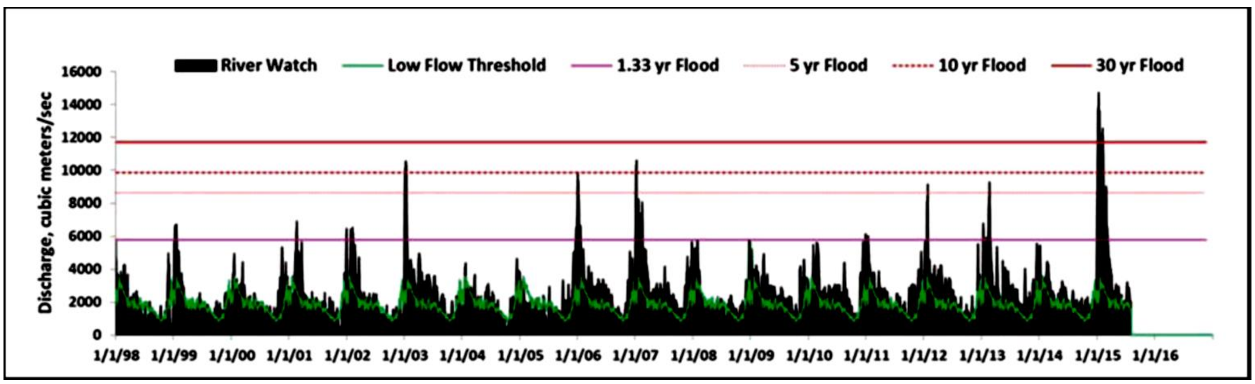


Figure 1.1Observed discharge for Shire River @Chiromo-the southmost gauging station and downstream of the confluence with Ruo River highlighting the extent of the extreme flood event of January 2015 in the basin (Figure adapted from the Malawi Hazard and Vulnerability Atlas)

The extent of damage that extreme floods may cause within the Shire River basin was deeply felt in January of the 2014/2015 season when heavy and intense storms spanning a number of days caused one of the most devastating floods in the country's history. The flooding was associated with torrential rainfall at the beginning of January 2015 and spanning for a number of days. The damage, as reported in both the Malawi Vulnerability Assessment Committee (MVAC) and Post-Disaster Needs Assessment reports was widespread, affecting different sectors of the economy and people's livelihoods with around 150 fatalities reported too. The estimated loss was $335 million which is equivalent to 6% of the country's GDP (Malawi Post Disaster Needs Assessment Report, 2015). The costs that would be incurred in recovery were even higher and magnified due to a major drought that followed in 2016. The flood recovery programme was actually still running at the time of writing this report-over three years after the occurrence of the flood. The extremity of the 2015 flood heightened attention towards climate change and facilitated the adoption of important policies such as the disaster risk reduction and management policy and the climate change management policy the year later. Whether climate change from anthropogenic emissions had a hand in the occurrence of the event is an important question from both academic and practical points of view.

1.4 Applying Event Attribution Concepts in Flood Risk Analysis in the Shire River Basin

In this study, a risk-based extreme event attribution methodology was used to determine the chance of an extreme flood event occurring in two different climates; the current climate, and a hypothetical climate resembling the climate as it would have been had it not been for anthropogenic greenhouse gas emissions. The study was based on the concept of fraction of attributable risk described by Allen (2003). However, noting the importance of other external factors in influencing the risk of flooding, a joint attribution was done to determine how the risk of experiencing a flood of a certain magnitude changes under two different climate scenarios and two different states of land use and cover. The motivation behind this joint attribution is described in subsequent sections. A detailed reflection of the science of attribution in climate science is given in the literature review while the methodology gives a detailed account of the experimental procedure.

The extreme event attribution methodology has so far been used to determine how the risk or likelihood of an extreme event might have been altered due to anthropogenic GHG emissions. The attribution question was originally posed in the context of so called "loss and damage" processes, i.e. obtaining compensation for losses incurred during extreme weather events attributable to climate change. Those held liable would be companies and other investments that contribute towards GHG emissions. A holistic view of the risk factors however, has one questioning the extent to which such extreme events should be attributed to climate change alone without considering other equally important factors. In his paper, *"liability for climate change",* Allen, (2003) posed the same question indicating how courts and insurance companies would be hesitant to pay out compensation for a climate change related damage while knowing that other factors such as changes in the catchment characteristics might be equally (even more) important in influencing the occurrence of such extremes.

To attempt such challenges disaggregated or joint attribution study, the risk-based methodology was used to evaluate the proportion of an event's risk attributable to two risk factors namely climate change from anthropogenic GHG emissions and land use and cover change. In the joint attribution process, this study attempted to use the concept generally employed for extreme event attribution but in the context of another changing risk factor in which case it would be determined how the factors jointly influence the risk of extreme events and the relative contribution of each while being able to disaggregate the contribution of each of the two risk factors to the likelihood of experiencing a flood of such a magnitude. The 2015 flood event and the rampant change is land use in the basin provide an ideal case for exploring the attribution question from a multiple risk factor point of view. Beyond the methodological challenge surrounding event attribution in the context of multiple risk factors, the study provides a good basis for flood risk reduction and management.

Both observation and climate models provide essential tools for exploring this problem even though the former is constrained by short observation periods from which to make generalised conclusions about the climate behaviour and hydrological responses to the same. In Malawi, and Africa in general, observation data is a huge limitation not just in terms of quantity but quality too. Climate models, on the other hand, provide a useful means for understanding the climate system and how its changes influence hydrological processes and extreme events such as floods. Particular to extreme event attribution, the concept of fraction of attributable risk (IPCC, 2014) provides a basis for exploring the additional risk from anthropogenic climate change against the background of risks naturally embedded in the system. This study, using the results from a hydrological model driven by climate model outputs, determined the extent to which the 2015 flood can be attributed to climate change under conditions of changing land use and cover. The hydrological and climate models as well as their set up and configuration are described in detail in the methods.

The rest of this dissertation comprises the literature review in the immediate chapter which includes a synthesis of literature on the change in flood risk with climate change and land use and cover change; the anatomy of extreme events and the risk of extreme events in a warming climate; extreme event attribution and many issues surrounding the approaches to attribution. The literature review leads into the objectives, rationale and the research questions in chapter 3. Chapter 4 describes in detail the study area as well as the nature of the extreme event of January 2005 on the basis of observed rainfall and streamflow. Chapter 5 is the methodology and describes the research process giving a detailed description of the hydrological and climate models and their set up (as well as calibration of the hydrological model) while highlighting the data sources. Chapter 7 presents the results and discussion while chapter 6 provides a summary as well as conclusions and recommendations.

2 Literature Review

Attribution of extreme events has become one of the major areas subject to research interest in climate science-both physical and applied. As Hegerl (2015) notes, extreme events bring climate change into public's interest far more than changes in global mean temperature. This has driven worldwide research in exploring changes in frequency and intensity of such extremes. Interest has remarkably grown in attributing specific events or the risk of their occurrence to climate change. Floods are one of the most studied categories of extreme events and their relevance stems from the fact that their effects are the most devastating and account for most of the losses and deaths from weather extremes. The occurrence of floods is, however, driven by factors far more than just climate. As such analysing changes in flood risk has to encompass all other risk factors as much as possible. One of such risk factors is land use and land cover change. Attributing extreme events such as floods to climate change is therefore bound to an extent, by the extent to which those other factors can be accounted for. This chapter provides a background of the global and regional flood risk in a changing climate by reflecting on some of the fundamental literature and current state of knowledge. It also highlights the different approaches to modelling changes in run-off and discharge (the basis for flood estimation) in the context of climate change. The chapter also gives insights into extreme event attribution highlighting, inter alia, previous studies, approaches, and some of the challenges. That, and the realisation of attribution as a challenge and an area of growing research interest forms the basis on which this study is founded.

2.1 Extreme Events in a Warming Climate

Notwithstanding the growing body of literature and advances in climate science, it is not fully known whether the risk of extreme events will increase going into a warmer climate. As a matter of fact, weather extremes happen all the time even in an unchanging climate. However, given the overwhelming evidence that our climate is changing due to anthropogenic activities, it is vastly important to understand whether that will increase the risk of those extreme events. The increase in global temperature may translate to the increase in the upper extremes of temperature thus increasing the likelihood of heatwaves- a weather parameter directly related to temperature. With respect to moisture, it is known that the increase in temperature increase the water holding capacity of the atmosphere owing to an increase in the atmospheric vapor pressure (Clausius-Clapeyron rule) unmatched with a change in the relative humidity. Otto (2017) however concedes an important element in relation to the occurrence of extreme events acknowledging the role of circulations and all other process necessary in the production of weather systems and extreme events. As Sillmann et al. (2017) also highlight that *"the development of an extreme event depends on some or all of the following: a favorable initial state, the presence of large-scale drivers, and positive local feedbacks, as well as stochastic processes (noise)."* Figure 2.1 from Sillmann et al. (2017) illustrates how these factors interact to influence extreme events in time the understanding of which forms the basis for predicting these extreme events using climate model and a background for evaluating climate models on the basis of their ability to simulate the extreme events of interest.

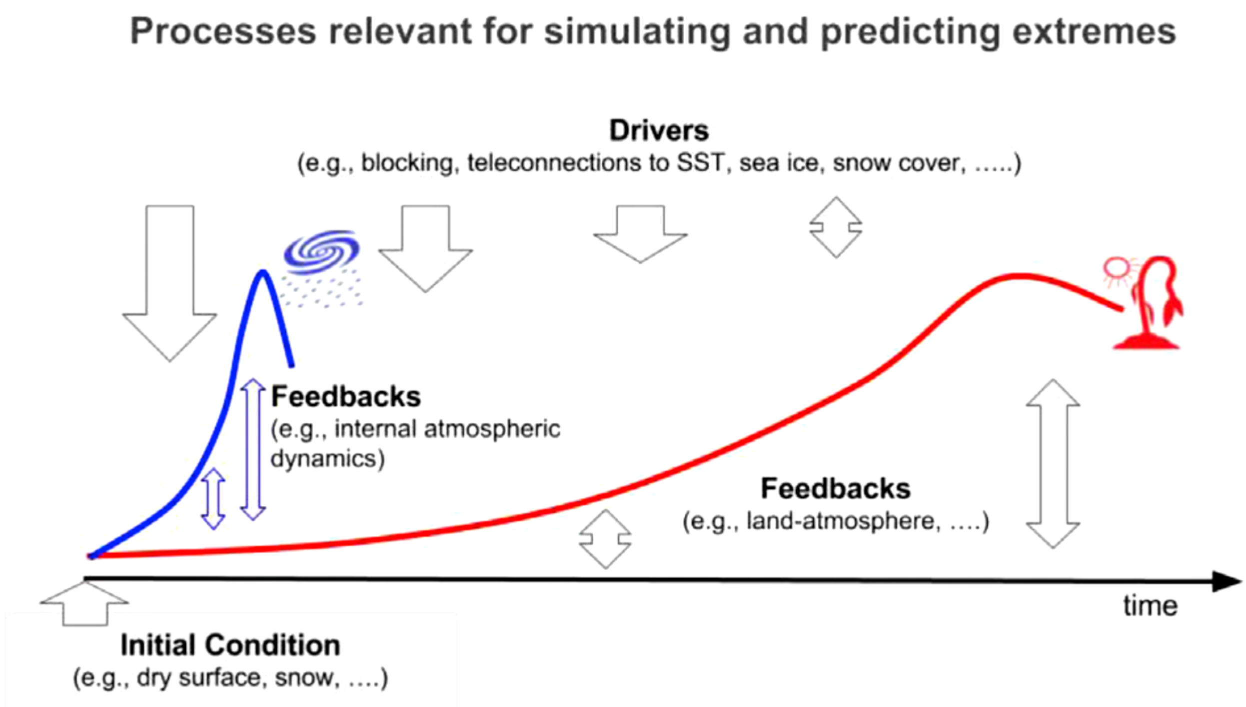


Figure 2.1Factors and processes necessary for the formation of extreme events as highlighted by Sillmann et al. (2017) *where the blue (short) curve represents short duration extreme events while the red (long) curve represents long duration extreme events*

Sillmann et al. (2017) highlighted the importance of these factors for different extreme events indicating that the relative importance of these factors depends on the extreme event which they are influencing. Extreme events occurring on shorter timescales, referred to as short duration extreme events (SDEs) are generally associated with an unstable atmosphere. These are the extreme events denoted by the blue curve in the illustration in figure 2.1. Such extreme events occur on a scale of up to 3 days and may include convective processes leading to heavy precipitation, hail, lightening, tornadoes and violent downdrafts; extratropical cyclones leading to wind storms, storm surges, extreme precipitation, freezing rain; anti-cyclones leading to fog and air pollution, cold outbreaks, long lived heatwaves and extended cold spells; tropical cyclones. On the other hand, long duration extreme events (LDEs) are generally associate with soil moisture-atmosphere interactions. Droughts, heatwaves, cold spells and floods caused by persistent rainfall fall in this category of extreme events.

External factors such as global warming from anthropogenic activities influence the occurrence of extreme events by enhancing the interactions between these factors. For instance, convective feedbacks can be enhanced due to the increase in moisture in the atmosphere as per Clausius-Clapeyron relationship. In the same way, enhanced evapotranspiration can also amplify the risk of extremes such as heatwaves and droughts. It is therefore of paramount importance to understand the role of global warming in altering the extreme events beyond a statistical point of view but on the basis of how global warming influence the factors, interactions and feedbacks too. While doing so, it important to recognize that the uniqueness of each and every extreme weather event given the different external drivers as well as climate variability and noise means that it is somehow difficult to generalise the risk of extreme events in terms of magnitude and frequency hence the need to understand each extreme event exclusive of another.

2.2 The Global Flood Risk in a Changing climate

Having looked at the literature on extreme events in general, it is vitally important to understand the flood risk in particular before attempting to understand the attribution literature. Intuitively, the risk of extremely intense rainfall should translate into the risk of flooding. Hydrological modelling provides the basis for understanding the impacts of climate change on hydrological systems, among which are extreme floods. Based on a synthesis of existing knowledge, the IPCC (2012) special report on climate extremes (SREX report) highlights, low confidence in the change in flood frequency and intensity at the global scale. However, Hirabayashi et al. (2013), noted that the limitations in terms of the evidence in the SREX can, to some extent, be attributed to the use of a single climate model in the study. Nonetheless, floods are considered one of the major climate related disasters with an expected increase in the frequency of high impact events. Associated losses and damages that have already increased drastically in the last couple of decades will likely increase too. Fischer and Knutti, (2015) highlight the possible changes in extreme flood events under different degrees of warming based on present day warming and an increase in warming by 2 and 3 degrees Celsius. The increase in precipitation extremes, as highlighted in their findings, would result in the likely increase in the extreme flood events.

The increasing global flood risk has also been demonstrated by Hirabayashi et al. (2013), who used 11 CMIP5 Model outputs for both historical and current climate as well as projections based on RCPs (Representative Concentration Pathways). Their findings highlight a significant increase in both the intensity and frequency of floods even though this is region-specific. The added value of their study is the fact they used a number of models all of which, for areas where there is projected change in frequency and intensity in floods, are consistent in the direction of change and remarkably so for RCP 8.5. Their challenge, however, as is with most hydrological models, was the relatively shorter observation period for river gauges for which to make an observation-based claim. This was countered by using the Gumbel distribution function which is effective for extreme distribution in relatively smaller samples. Chiew et al. (2009) demonstrates the utility of multi-model ensembles for simulating run-off in the context of Australia. Such multi-model combinations are either for the same climate model under different emissions or concentrations or different climate models for the same emission scenario or concentration of greenhouse gases.

A similar analysis (of using multi-model assessment) was done by Dankers et al. (2013), however, using outputs from Inter-Sector Impact Models Inter-Comparison Project (ISIMIP). The use of such models enabled them to not only simulate the global flood risk in a changing climate but also to explore and quantify the uncertainty from impact models. The findings from this study were also consistent to a great extent with Hirabayashi et al. (2013) findings even though they are constrained by the fact they only used RCP 8.5 scenario (as opposed to two scenarios experimented with by Hirabayashi et al. (2013)) for future projections (for the period 2071-2100). Their added value is nonetheless significant. It should be noted that, even though the direction of change was negative for some areas, these were largely those whose flow is largely influenced by snowmelt, which is not the case with African river basins. The study however also acknowledges the fact that results were subject to uncertainty arising from both climate and impact model uncertainties-which are even more pronounced in hydrological models given the limited ability to assess uncertainty in hydrological models.

The perspective of regional variations in the global context is highlighted by Arnell & Gosling {2013) who, from a more physically based analysis found that impacts of climate change are not necessarily dependent on changes in precipitation alone but on the context in which floods are generated too. Their analysis is largely tied to the distinction of processes that are influenced by snowmelt and those that are driven by precipitation-saturation relations. The extended analysis of context-specific processes is also relevant for large basins that have different sub-catchments such that, even though the climatic changes may be widely generalised at basin scale, the catchment-specific contexts may have a significant influence in flood generation and routing. Their analysis of flood hazards uses different indicators one of which is frequency. To determine this, they analysed using the generalised extreme values distribution fitted simulated annual maximum daily flows using L-Moments for a 100-year event as a reference event. Their findings in that regard highlight an increase in the frequency of these events-occurring twice as often-in 40% of the world and over 60% of central Africa. A further analysis looked at the changes in the numbers of people exposed to floods as an indicator for flood hazards which was found to be increasing where flood frequency was increasing relative to the 1961-1990 baseline used in the study

2.3 The Regional and Local Context

It is vitally important to understand the regional context of flood risk in a warming climate given the spatial scale of the factors that influence the risk. The general global picture is one of an increasing global flood risk associated with climate change. Regional climate change perspectives have been documented in Climate Risk and Vulnerability-a Handbook for Southern Africa by Davis-Reddy & Vincent (2017) and most recently updated in 2017. Climate Systems Analysis Group (CSAG) at University of Cape Town as well as the Council for Scientific and Industrial Research (CSIR) conduct comprehensive regional assessments and provide most of the climate information in the region. Recent studies through the Future Climate for Africa (FCFA) and World Climate Research Programme (WCRP)'s CORDEX project continue to provide and improve climate information for the region which has been limited and often relied on global scale assessments. Maidment et al (2015) highlight changes in rainfall patterns over most African regions with regional specific variations in the magnitude and direction of change as well and offering different explanations for the observed variability which is attributable to anthropogenic climate change in some areas and internal modes of variability in others.

With a few exceptions like Wolski et al (2014) and Ngongondo et al (2013) Ngongondo et al (2013), most hydrological assessments for the region are very much focused on water resources and less explicitly on extreme events, let alone attribution of such events to climate change. Kusangaya *et al.* (2014) reviews some of the studies that have been done across the climate change spectrum within the region with respect to water resources. Conway *et al.* (2015) and Aich *et al.* (2014) also provide some insights with regards to hydrological impacts of climate change in the region. Aich *et al.* (2014) studied the African perspective of climate change impacts on stream flow in four major "representative" catchments; Niger, Upper Blue Nile, Limpopo and Oubagui. Their study used the SWIM model set up for each of the four catchments and driven by outputs from five bias-corrected CMIP5 models to determine climate change impacts on stream flow for RCPs 8.5 and 2.6. Their study is of remarkable relevance in highlighting the representativeness of the GCM's and their skill to adequately make regional projections relevant for impact modelling. Inevitably, the level of uncertainty for all the basins in the experiment is high. The impact of climate change on stream flow is, nonetheless, visible and more so for extreme lows and highs, the latter which is vital for predicting floods. Key to the modelling of the hydrological changes, where the focus is largely on extreme highs and lows, is the generalisation that precipitation and temperature are the major drivers of hydrological regimes underlying the importance of climate change to the question of attribution as its impacts are largely felt through changes in these two variables.

Jury (2014) explores the impacts of climate change on streamflow fluctuations in the Shire River. The study highlights the different hydrodynamics of the Shire River and different factors that influence flow at different points. Using measurements from four gauging stations placed at approximately 100 kilometres apart, she identified different responses of streamflow as measured at these stations and influenced mostly by lake levels (for Lake Malawi) and buffering in the upper section (Mangochi) and valley run-off in the middle and lower sections. Particular to floods, she noted the coincidence of the occurrence in extreme highs with a cyclonic looping wind pattern that subsequently amplifies the equatorial trough and draws monsoon from Tanzania and in some cases a tropical cyclone from Madagascar. Teleconnections with global phenomena such as the Pacific cool La Nina also have an impact on local precipitation and subsequent stream flow responses.

The perspective of land use change has been relatively less studied. Studying in the context of South Africa, Warburton, Schulze, & Jewitt (2012), explores the impacts of land use and cover change on hydrological responsiveness and how that might modify hydrological impacts of climate change. Their results, based on the ACRU model, highlight that the responsiveness of all the sampled catchments is dependent on the interaction of both climate and land use characteristics. Specific to Malawi, the results of a SWAT model run by Palamuleni, Ndomba and Annegarn, (2011) highlight the impacts of land cover change on the hydrological regimes in the upper Shire River Basin. The change in land use and cover is particularly driven by growing population and the need to expand production and settlements even though climatic variability is cited to contribute to such changes too. Evidence suggests that such changes in land use and cover have led to changes in different hydrological processes such as evapotranspiration, and most importantly in this case, peak flow intensity and frequency. The most notable changes were the replacement of woodlands with cropland and the over-grazing of dambos consequently rendering them bare, a phenomenon also notable for cases of massive harvesting of forests for fuel wood. Even though the study is concentrated to an area in the upper part of the Shire River basin, the results are, nonetheless, indicative of the likely changes in hydrological regimes throughout as a result of land cover change and reflective of the realities driving such changes in the basin.

Elsewhere Li *et al.* (2009) highlight the relevance of understanding climate change and land use change as occurring in the context of each other and having a combined effect on the hydrological processes of a catchment. Their case study, based in China's Pyoyang Lake basin, evaluates the impact of each of the two factors by making four runs of the SWAT model- a preferred methodology of time series analysis and the paired catchment approach. The four runs are a combination of two different climates (represented by two time-slices) and land use types of those two time-periods. The impact of climate change, independent of land use and cover change is analysed by holding land use constant and comparing the varied climates for the two time-slices. In the same way, the impact of land use is observed where climate was kept constant and land use varied for the two different time slices. The impact was greater where both climate and land use had been changed highlighting the amplification of the risk when the two factors interact. The findings from this study were generally consistent with other studies even though the methodology used might not adequately depict human-induced climate change.

Studying such regional processes has to some extent been impeded by the fact that the African climate is understudied, even more so the Southern African domain. The Shire river basin is thus situated in a region where future climate information is not as robust. While, for the region, climate models consistently predict warming, the direction and degree of change with regards to precipitation is with huge uncertainty. The increase in temperature increases the atmosphere's water-holding capacity but there is more to rainfall driving mechanisms and moisture transfer into the atmosphere given the complexity of the nature of the hydrological cycle. Changes in rainfall characteristics such as amount, event duration as well intensity, would have profound consequences on hydrological processes among them runoff and discharge as well as the risk of flooding. A careful analysis of the observed rainfall has to be done to determine whether there has been a change in these characteristics and whether such changes would be sustained as the climate warms further. Most importantly, the impact of such changes on hydrological processes and the likelihood of extreme events with a significant damage to people's livelihoods, life and other systems.

The relevance of climate change to these communities has seen an increase in the efforts to better understand the climate of the area as well as the broader African climate, which is the least understood-hence not best represented in climate models. One of such projects is the UMFULA project under the broader Future Climate for Africa programme. Model evaluations have been done to determine and select models that best represent the region through a process-based evaluation of the models that participated in the CMIP-5. However, in the context of this project, the HadAMP3P was used drive the hydrological model from which streamflow data was derived for the attribution procedure. Unlike the coupled models participating in the CMIP-5 experiment, The HadAM3p is an atmospheric general climate model. It is a standard model for attribution experiments and has been used for attribution work within this region of Africa Wolski *et al.* (2014) with bias corrected rainfall. A detailed description of the model will be given in the methodology however this section justifies that the model was fit for purpose as far as this work was concerned.

2.4 Event Attribution to Anthropogenic Greenhouse Gas Emissions

In light of climate change and an anticipated increase in the likelihood of extreme events, the interest in events, rather than trends has been increasing with a growing body of research and knowledge in event attribution (Jentsch, Kreyling, & Beierkuhnlein, 2007; National Academies of Science Engineering and Medicine, 2016; Zwiers et al., 2013). Extreme events such as heat waves in Russia and record high temperatures in central England have been particularly studied (Hegerl, 2015; Herring, Hoerling, Kossin, Peterson, & Stott, 2015; King, Van Oldenborgh, Karoly, Lewis, & Cullen, 2015; Stott et al., 2016). Kay *et al.* (2011) also highlight, in the context of the 2000 autumn/winter flooding in England and Wales, the increased likelihood of extreme events in a warmer climate. Attribution is the process of evaluating the relative contributions of multiple causal factors to a change or an event with an assignment of statistical confidence (National Academies of Science Engineering and Medicine, 2016). In the context of climate change, attribution dwells on evaluating the relative contribution of climate change-driven by human emissions of greenhouse gases-to the likelihood of occurrence of the extreme event in question. By way of analysing the exceedance probability of a threshold-set around the magnitude of the extreme event in question-attribution studies sought to determine the change in the likelihood of exceeding that threshold under different climatic conditions; the “factual” and “counter-factual”. The “factual” climate is the current climate, forced by both natural and human forcings (emissions) while “counter-factual” climate is the hypothesised state of the climate that could have been in the absence of human emissions of greenhouse gases. The latter allows for making an assessment of the likelihood of exceeding an event’s threshold in the absence of the role of climate change (King et al., 2015).

Quite a number of attribution studies have been undertaken since a methodology was proposed by Allen (2003). Among the most studied extreme events in the context of attribution have been the Russian heatwave of 2010, the Californian drought, the central European extreme temperature, the autumn flood of 2002 in the UK and Wale among others. The methodologies for attribution experiments have also been interrogated and evaluated and continue to be improved to ensure that there is both improved understanding of the extreme events and the confidence in the attribution of those events or the risk of them occurring due to climate change (Otto, 2017; Sillmann et al., 2017). In both elements of the attribution experiments, sound modelling-both climate and impact modelling where the event in question would be understood by the latter-and statistical analysis is essential. Some studies have combined both experiments and statistical analyses (King et al., 2015) but a majority have been done based on the “factual”-“counter-factual” methodology the analysis of which, for the risk-based approach, involves calculating the proportion of the risk attributable to climate change. Such analyses are performed on climate simulations based conditioned on different atmospheric states with one closely representing the current state of greenhouse gas emissions and another approximating what the state of emissions could have been had it not been for anthropogenic influences.

2.4.1 History and Applications

Prior to Allen's publication in 2003, attribution studies had only been conducted from a trends point of view, in studies generally known as detection and attribution. Allen's paper provided the foreground for attribution experiments with a focus on particular events. By determining how the risk of that event occurring changes with changes in forcings, scientists would be able to determine whether climate change might have had a hand in occurrence of the event. The motivation was primarily based on being able to insure assets against climate change and to come up with better insurance policies such that property owners would be compensated for their losses during an extreme event on the basis of anthropogenic climate change. The science of attribution has been used to understand whether climate change has been responsible for certain extreme events and to what extent. The same methodology has been applied to climate projections to determine how the risk of such an event changes under different future climate scenarios as demonstrated by Fischer and Knutti (2015). Beyond the science realms, attributions studies also sought to understand how responsibility can be assigned for losses and damages incurred during extreme events.

2.4.2 Regional Context of Attribution Studies

The recently published SADC handbook on climate risk and vulnerability (Davis-Reddy & Vincent, 2017) indicates an increase in the frequency and magnitude of extreme events as well as the damages and losses associated with climate related disasters across the region. Despite the increase in the number of extreme events of importance to the region, there has not been many attribution studies done within the southern African region. Wolski *et al.* (2014) is one of the few attribution studies in the region and one which sets the precedence for this study with regards to the experimental procedure. Other studies include Angélil, Stone and Pall (2014) and Lott *et al.* (2014) both of which do not necessarily focus on a particular event but rather the applicability of the procedure to the region and the reliability of the results of attribution studies on the basis of the methodologies currently available. The former particularly focuses on South Africa and explores, using s risk ratio approach, whether certain indices representing extreme events change in the GHG and non-GHG simulations which represent the "factual" and "counter-factual" climatic states. Their study is fundamentally based on Pall *et al.* (2011) but adds an extra layer of value by comparing the results of the simulations and calculation of risk ratio on spatial scale in the context of South Africa. Wolski *et al.* (2014) is perhaps the flagship study in attribution and more so for the risk of flooding in a changing climate. It also provides a learning case where in what could be thought of as counter-intuitive, the risk of flooding in the studied basin (the Okavango) was rather smaller in the current climate as compared to the one with no anthropogenic emissions. The basis for that study was the HadAM3p run within a CSAG following an innovative seasonally-based approach (Stone et al 2014) rather than the traditional multi-century simulations.

Otto *et al.* (2015) have highlighted on the potential that event attribution studies have on enhancing effective adaptation to the climate change impacts in the region. They particularly noted the limited focus on event attribution studies relating to the limited focus on studies in understanding the African climate in general. Extreme event studies in the African context already face a limitation given the observation constraints and limitation in terms of climate model simulation of most domains within Africa, a view also shared with Angélil, Stone and Pall, (2014) and Lott *et al.* (2014), particularly so for rainfall which of key interest to this study. However, the role of SST on African rainfall variability has been demonstrated which indicates the potential for confidently simulating extreme events in several domains within Africa by prescribing SSTs in an atmosphere-only models such as that which was used in this study. Nonetheless, Otto *et al.* (2015) conceded the fact that by then not many event attribution studies had been done within the region partly due to the fact the methodology had only been recently developed.

2.4.3 Approaches to Extreme Event Attribution

Otto, (2017) highlights three main approaches to attribution studies thus far. These are namely the risk-based or Oxford approach, the Boulder approach and the analogy approach. This particular study uses the risk-based (Oxford) approach as such the review of approaches to extreme event attribution particularly focuses on that and not the other two. In the risk-based approach, the underlying concept is the fraction of attributable risk define by Allen (2003). In this approach, using either climate modelling or empirical modelling approaches, the key undertaking is to determine how the likelihood of experiencing an extreme event of a given magnitude changes in two climate scenarios; the current or "factual" climate and the preindustrial or "counter-factual" climate. Where climate models are employed, both coupled and atmosphere only global climate models with the latter being widely used given the feasibility in terms of running multiple ensembles.

2.4.3.1 FAR Concept

The underlying principle for event attribution studies based on the probabilistic event attribution (PEA) or risk-based (oxford) approach is the determination of the fraction of attributable risk (FAR). This is the proportion of the risk which can be attributed to anthropogenic emissions based on comparing probability distributions of the variable of interest in two or more climate states to one another. The relationship between the probability distributions is illustrated in figure 2.2 below, whose mathematical relationships are explained in detail in the methodology. It is not always necessarily the case to find that climate change should lead to an increase in the likelihood of an extreme event or that it should be thought as counter-intuitive that the likelihood of that event occurring actually diminishes as the climate warms. Such findings are possible as has been found by Wolski *et al.* (2014) who, in the context of the Okabvango region, the likelihood of the 2011 flood was found to be lower in the current climate as compared to a preindustrial climate scenario. Thus, there are generally four outcomes in attributions studies; the event being more likely as a result of anthropogenic climate change; ii) the event being made less likely as a result of anthropogenic climate change; iii) no detectable influence from climate change; iv) current tools and knowledge not being sufficient to help us analyse the role of external drivers on the event. Crucial for the whole process is to be able to determine the proportion of the change in risk associated to anthropogenic climate change and the confidence in the conclusion made about that fraction of attributable risk.

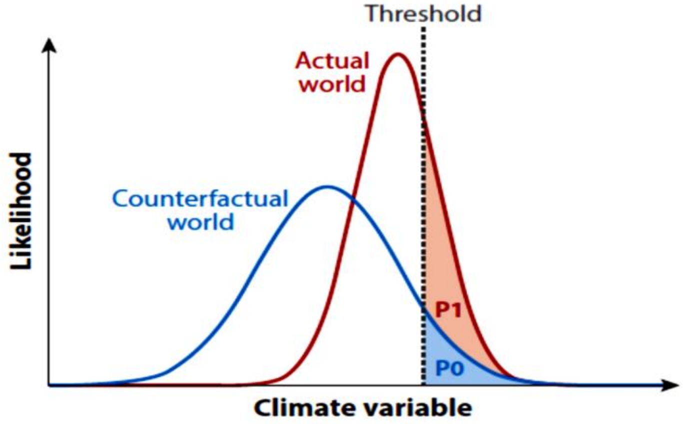


Figure 2.2 Schematic for determination of the Fraction of Attributable Risk of an extreme event of a predetermined threshold. The FAR is determined by comparing the excedance probability of that event in the two climate states-the current climate (factual)

and the preinsustrial climate (the counterfactual world). The shapes of the distribution can change in various ways depending on how the mean and variability of the variable of interest changes in the two climate states (Allen, 2003) and the FAR is determined from the relationship between P0 and P1 which denoted the probability of exceeding a threshold value for a climate variable in the counterfactual and factual climates respectively. (Figure sourced from.(Otto, 2017)*)*

2.4.3.2 Modelling Framework

The basic modelling approach is to run simulations of the "factual" and "counter-factual" climates. The climate model simulations are therefore done in such a way that in the "factual" climate scenario, the model is forced with atmospheric conditions closely resembling the atmospheric composition during the period of the occurrence of the event while the "counter-factual" simulation is forced with emissions from natural sources only generally following the procedure laid out in CMIP 5 for the Historical Nat simulations (Otto, 2017). To counter chaos and stochasticity, ensembles are often used in which case multiple simulations are done with different initial conditions. Where the feasibility permits, multi-model ensembles are also used which help to minimise limitations due to climate model inadequacies. Feasibility also determines experimental set up by influencing the choice of such elements as resolution, dynamics and length of simulations (Pall 2010, Stone *et al.,* 2014, Wolski *et al*., 2014). A distinction in making such a choice for experimental set up is seen in Stone et al. (2014) in their application of the HadAM3p for an attribution experiment. In this study, a seasonal forecast attribution model set up was used. A full description of the process is given in Stone *et al*. (2014) while a summary of the same is given in section 5.2 of this report.

The same concept of running a climate model in two different states is applied for attribution studies based on climate impact assessment models. In such cases attribution studies undertake to run two sets of climate impact model simulations driven by outputs from climate model simulations run in the "factual" and "counter-factual" modes as demonstrated by (Fischer & Knutti, 2015; Pall et al., 2011; Wolski et al., 2014). In such cases, a variable or index used to quantify the event is chosen for the statistical analysis used to determine the likelihood changes from which the FARs are derived. In case of floods, the analysis if applied to run-off, or just the annual peaks from the two sets of simulations while drought analyses often apply indices such as the Palmer drought severity index and the standard precipitation.

Probabilistic event attribution experiments also generally require processing the climate model outputs prior to their analyses, or use for climate impact model simulations, through various statistical downscaling procedures as highlighted by Otto, (2017), Wolski *et al.* (2014) and Pall *et al.* (2011). Model evaluation and bias correction are an important step in the attribution process and are an integral part of any attribution experiment. Post-processing of climate model outputs (or pre-processing of climate impact model forcing data) is particularly important for attributions studies based on climate impact models given the transferability or 'cascade of uncertainty' from climate models to climate impact models. (Sillmann et al., 2017) highlight how models are necessarily imperfect and that they may not be able to reproduce all extreme events, but they should at least be able to reproduce the extreme events of interest and over the domain of interest too. On the basis of large-scale drivers, dynamic and thermodynamic processes should ideally be separated, generally artificially, given that dynamical changes are influenced by thermodynamic processes. Such processes are not easy to unravel in climate models. Equally difficult is the representation of feedbacks that may influence the mechanisms for extreme events. It is because of such imperfections that choice of model should be based on its ability to reproduce processes and statistics of interest. To that effect, Otto (2017) recommends that model evaluation and a physically meaningful bias correction should be an integral part of any attribution study.

2.4.3.3 Determining the Proportion of Risk Attributable to GHGs

To determine whether there is a proportion of the risk attributable to climate change from anthropogenic GHG emissions, a probability distribution function is fitted to the variable of interest. The exceedance probability for an event of a predetermined threshold is determined for both "factual" and "counter-factual" sets of outputs as illustrated in figure 2.2 (for the exceedance probability of an event in the counterfactual and factual worlds). By analysing the distribution of the probability of experiencing a specified extreme event in the "factual" and "counter-factual" climates, conclusions can be made as to whether the odds of experiencing such an event have changed as a result of climate change. This is often determined through the probability ratio which relates the probability distribution functions of the event in question under different climates (Fischer & Knutti, 2015). The concept of Fraction of Attributable Risk (FAR) has been widely used to determine the change in the risk of the occurrence of an event attributable to climate change (King et al., 2015; Pall et al., 2011; Stott et al., 2016). (Fischer & Knutti, 2015) also used similar frameworks but highlight, in the global context, the percentile range of extreme events attributable to climate change at different degrees of warming. The concepts of probability ratio and fraction of attributable risk will be further discussed in the methodology. Wolski *et al.* (2014) have studied the attribution of floods in the Okabvango basin on the basis of these approaches too in which case they established that the likelihood of flooding-specified for the 2008-2011 period-was lower in the current climate as compared to the "counter-factual" climate.

To an extent, how one answers or interprets findings from an attribution experiment is dependent on how the attribution question was framed as Otto (2017) highlights. In the same paper, she also highlights how conditioning the experiment on observed SST versus conditioning it on long term warming might affect the results and consequently the conclusion too. Other than the framing of the question, its definition matters too. The definition of the event and how that could make the results differ from the point of exceeding a threshold. For instance, whether one has to define the event as the likelihood of a heat wave of a certain magnitude or whether it is defined in terms of changes in the heat stress on the body in which case the latter might give a smaller anthropogenic signal. The framing as well as the definition of the extreme were carefully considered in this study.

In general, therefore, there are six key steps that are undertaken in risk-based approach for extreme events as indicated by Otto (2017).

1. Description of what happened; this involves giving a background a description of the extreme event based on observations and reanalysis as well as reports on impacts.
2. Event definition; the definition of the extreme event and the region in which it occurred, the variables of interest (meteorological, hydrological or other variables based on the extreme event being studied) and the rarity of the event. In this case one analyses the available observation data directly relating to the event in which case one also sets the threshold, based on the magnitude of the event, for which to determine the exceedance probability and the fraction of attributable risk.
3. Model evaluation; evaluating the model on the basis of its reproduction of the key processes and statistics. This aids the bias correction and downscaling processes.
4. Estimate likelihoods; Following the running of the model, the variables of interest are analyzed to determine whether the mean and variability of the variable changes with scenario and thus whether an event of the specified threshold changes with scenario.
5. Interpret and synthesize; interpret the results from the previous step and determine whether there is change in the risk of the occurrence of the event attributable to anthropogenic greenhouse gas emissions while determining the confidence in the attribution too.

6. Communicate the results, uncertainty and confidence based on the question that was being asked

2.4.4 Challenges in Probabilistic Event Attribution

Challenges in terms of understanding and explaining the causes of the extreme events as well as the confidence with which they can be attributed to climate change underline the relevance in the growing interest in the field of attribution. Figure 2.3 highlights this challenge which is specific for each extreme event. The occurrence of a particular event, driven by chance, is very difficult to attribute to climate change. In essence, attribution is described in two aspects; attribution of an event in particular to a specific weather or climate process or the role of human activity in the actual event-in such cases where the objective is to understand the role of human induced climate change on the occurrence of such events (Trenberth et al., 2015). Hegerl, (2015) summarises the challenge that is extreme event attribution and more so for short-lived extreme events where challenges stem from both observational and model inadequacies. Her view of extreme event attribution echoes the influx of studies that have been conducted in recent years focusing specially on extreme event attribution through statistical applications. Many attribution studies focus on the changes in the probability of occurrence of an event.

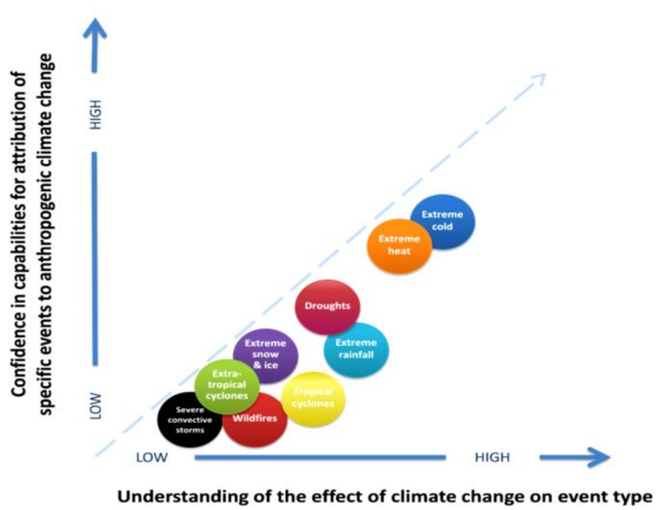


Figure 2.3 Challenges in extreme event attribution (Source: (National Academies of Science Engineering and Medicine, 2016)*).*

2.4.5 Towards a Joint Attribution Approach

From an "impacts" perspective, extreme events are often bound by other factors other than climate change and comprehensive analyses have to accommodate the possibility of the influence of other drivers on the risk of occurrence of the event. While other drivers may not necessarily affect the odds of the event, their impact may be manifested through magnifying its magnitude and intensity. The magnitude of heatwaves, for instance, may be amplified by other factors such as urban heat island effect. Extreme flooding, as driven by extreme precipitation from a climate perspective, may be influenced by changes in land use or other human impacts such as river channelling, development of impervious surfaces and even flood control infrastructure upstream which may magnify the magnitude of the flood downstream. Trenberth, Fasullo and Shepherd, (2015) also highlight the challenges associated with attribution from an impact point of view highlighting how the extent of the damage does not always depend on the magnitude of the event but rather acts as a function of exposure and vulnerability too. Otto (2017) concurs with the same view and highlights how a large meteorological signal does not always translate into a change in the impacts and whether it depends to a large degree on the vulnerability and exposure of the system as much as it depends on the meteorological hazard in which a case a holistic attribution study would need to look at both.

Studies analysing the influences of climate change and land use and cover change have been done(Guo, Hu, & Jiang, 2008; Natkhin, Dietrich, Schäfer, & Lischeid, 2015; Yengoh, Fogwe, & Armah, 2017) however with more focus on trends rather than events, let alone from an attribution point of view. Joint attribution of land use and cover change and climate change impacts on flood risk remains an area of subject to research interest with the attribution methodology often limiting analyses towards assigning a proportion of the risk to climate change, nonetheless recommending the need for more encompassing risk assessment to improve the confidence in the attribution. Given the fact that runoff generation is a function of both storm and land characteristics that determine the runoff coefficient (the amount of precipitation that effectively forms runoff), exploring the risk of both factors would count for more robust analyses and well-informed flood mitigation measures through measures such as catchment management and flood mitigation infrastructure.

As established in this background, climate change and land use and cover change both have the potential to influence the risk of flooding while also modulating each other's impact on the risk of extreme events. This study attempted to establish, in the context of the 2015 flood in the Shire River basin, the impact of climate change on the risk of extreme flood events under conditions of changing land use as an important risk factor too. A similar joint attribution experiment was attempted in the Okabvango delta flood attribution study by Wolski *et al.* (2014). However, their joint attribution was on the basis of two meteorological factors namely rainfall and temperature. The underlying rationale was that both temperature and rainfall influence run-off as the former regulates water balance through evapotranspiration. In the context of the current study, joint attribution is perceived as the process of determining the relative contribution to the likelihood of exceeding an extreme event (flood) of a given magnitude by climate change and other external factors (land use and cover change in this particular case).

3 Study Aim, Objectives and Research Questions

The aim of the research was to use the concept of FAR to determine the extent to which the flood experienced in 2015 in the Shire River basin could be attributed to climate change given that land use and cover change-an important risk factor-is evident in the basin too. Using outputs from a global climate model to drive a hydrological (rainfall-runoff) model, the study particularly focused on this specific event given that it had not been studied from an attribution point of view leaving a number of lingering questions unaddressed in that regard. The uniqueness of the event is such it was described by the department of disaster management as the worst on record while the land use history also provides an opportunity an opportunity for exploring the joint attribution question. The research aims at contributing towards the growing body of research in the extreme event attribution frontier of climate science. The element of joint attribution is an added value given the importance of both drivers (climate change and land use and cover change) as well questions that are asked about other external factors in attribution experiments. Findings from the study may also be used in policy and development decision making mostly around flood mitigation and other land use related decisions.

3.1 Main Objective

The main objective of the study was;

- to assess the implication of climate change and land use and cover change on the risk of extreme flood events in the Shire River basin

3.2 Specific Objectives

Specifically, the study seeks to;

- Determine the relative contribution of climate change and land use and cover change on the risk of the 2015 flood in the Shire river basin
- Evaluate the impact of observation limitations in joint attribution of extreme events given the observation limitations that characterise the region

3.3 Research Questions

The main research question is to understand how the exceedance probability of the 2015 flood in the Shire River basin is influenced by human-induced climate change under different conditions of land use. The specific research questions are;

1. What is the likelihood (exceedance probability) of the 2015-flood event in a pre-industrial (counter-factual) climate under different land use scenarios?
2. What is the likelihood (exceedance probability) of the 2015-flood event in current climate (factual) under different land use scenarios?
3. What is the fraction of the risk of the “2015 flood” attributable to climate change and land use and cover change?
4. To what extent does climate change and LUCC amplify or dampen each other’s risk on extreme flooding in the Shire River basin?
5. How do data constraints associated with typical data availability challenges in African countries limit the attribution of extreme events to climate change?

4 Study Area and Event Description

While focusing on the Shire River basin wider context, the modelling and attribution processes were specifically done for the Ruo River basin, the biggest, and one of the most important tributaries, of the Shire River basin. This chapter gives a detailed description of the study area describing, among other things, the climate, hydrology, and state of land use in the basin. It further describes the extreme event in terms of the nature of its extremity in relation to long term observations. Characterisation and definition of the event is based on both observed rainfall and streamflow during the time of the occurrence of the event in relation to observation records available from 1981. Data sources and the quality of data for the characterisation and definition processes are discussed in the next chapter. However, it should be mentioned outright that streamflow data for the most downstream station of the Ruo River was only available up to 1991 as such the event definition process largely depended on pseudo data generated from the hydrological model used in this study. In a way, this chapter is the first step in the step by step attribution process described in section 2.4.3.3.

4.1 Description of the Study Area

The Shire River is the single outlet for Lake Malawi running for approximately 520 kilometres and draining into the Zambezi River in Mozambique (Shire River Basin Atlas, 2016). Shire River is thus a tributary of the Zambezi and, together with other tributaries, form the fourth largest river basin in Africa and the largest in Southern Africa. The Shire River is considered in three phases-the upper Shire River, the middle Shire River and the lower Shire Valley. The Lower Shire Valley is particularly vulnerable to extreme floods in extremely wet seasons. The upper Shire River exits Lake Malawi and flows over a gentle slope through Lake Malombe (a shallow lake a few miles south of Lake Malawi) and up to the Liwonde Barrage which is used to regulate water levels in the river generally for purposes of electricity generation in the middle part of the river. The Middle Shire runs from the barrage to Kapichira falls further south. There is no much descent in approximately 50 km, estimated at seven meters. The river then drops steeply by 360 metres over a distance of around 70 km through a series of rapids and falls some of which have been harnessed to provide run-of-river hydropower. The Lower Shire emerges below the falls at Kapichira to flow across a wide floodplain, in which the Elephant marshes are located, before exiting to Mozambique.

Several rivers, both perennial and ephemeral, drain into the Shire River forming a dense network of sub-catchments with a surface area of about 22, 317 km2. The major sub-basins include Ruo, Rivirivi, Lisungwe, Mwanza, Wamkulu Madzi, and Thangadzi. Given the complexity and size of the Shire River basin, one sub-catchment, Ruo, was selected for this study. The Ruo River is the largest tributary to the Shire in terms of both the amount of discharge and the catchment area drained by a sub-catchment of the main basin. Two main rivers from part of the Ruo catchment; the Ruo river itself and its main tributary-Thuchira. Both rivers have other small tributaries. The Ruo catchment, like other catchments within the basin, has undergone considerable degradation over the last two or so decades with the dominant land use changing from forest (dense or sparse) to crop land; perennial and seasonal. Of the main sub-catchments making up the Shire River basin, Ruo occurs at the most downstream. It drains into the Shire River at a confluence just before Chiromo, which is the most downstream hydrometric station along the Shire. Runoff from the Ruo river basin makes a substantial contribution to peak flooding in the Lower Shire Valley which is often the worst hit in terms of floods and so was the case for the 2015 flood. Despite its relevant contribution to the Shire river flows and dynamics at the confluence with the Shire and downstream, the Ruo catchment remains understudied as it is mostly studied in the context of the Shire River basin which, in itself, is also often studied in the broader context of the Zambezi river basin. The spatial and temporal scale in terms of land use and cover change as well as the rainfall patterns, and most importantly the extreme events of

2015 are such that findings specific for the Ruo can to some extent be generalised for the Shire River basin even though studies focusing on the main basin where feasibility permits would be recommended.

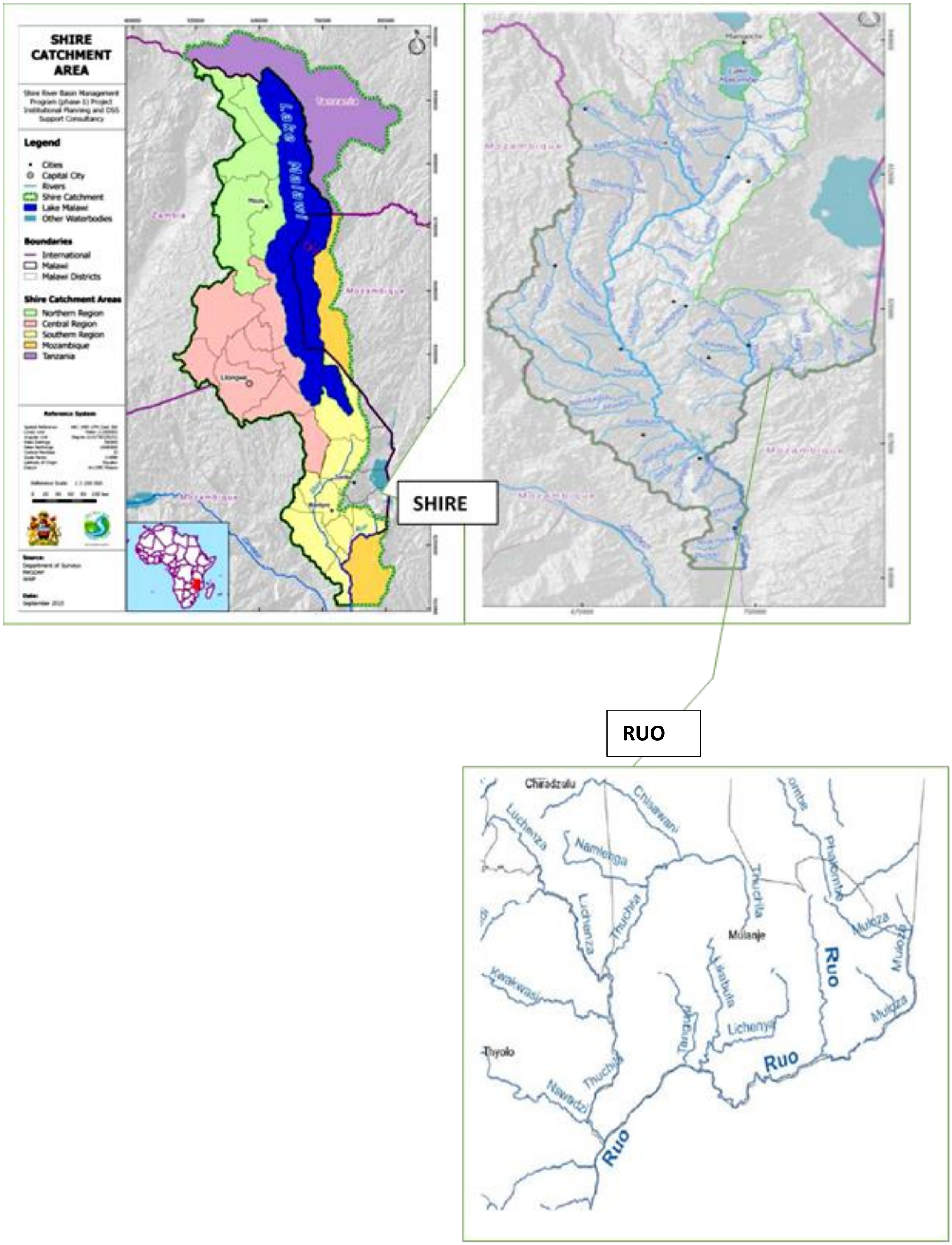


Figure 4.1 The Shire river and basin and the Ruo sub catchment

4.2 Climate, Hydrology and Land Use in the Shire River Basin

Malawi climate is subtropical characterised by two major seasons-the wet season from November to April and the dry season from May to October. Local patterns and variability are largely influenced by altitude and proximity to Lake Malawi. The Inter-Tropical Convergence Zone (ITCZ) is the main rainfall bearing mechanism whose movement (relocation from the equator to the southern tropics) varies with years. Most of the rainfall is received between December and February. Tropical cyclones are also an important mechanism influencing rainfall in Malawi and mostly so in the southern part of the country (in the Shire river basin region) given the propagation of storms in the Mozambican channel as they develop from tropical cyclones developing off the Mozambican coast in the Indian Ocean. The tropical cyclones form over the Indian Ocean and move eastward bringing widespread heavy rainfall that is also associated with flooding in the Shire River basin, particularly in the Lower Shire Valley. Other mechanisms include the convergence ahead of pressure surges and the easterly wave systems which bring locally isolated but heavy rainfall just before the onset and towards the end of the rainfall season respectively. Indian Ocean sea surface temperatures (SST) and other phenomena such as ENSO (El Nino Southern Oscillations) influence rainfall variability on inter-annual time scales. In general, ENSO teleconnections are such that eastern equatorial Africa usually receives above normal rainfall while south-eastern Africa experiences rainfall deficits in the warm phase while the opposite happens in the reversal (La Nina) phase. Malawi lies along the boundary of regions with contrasting ENSO responses such that the northern part experiences wetter conditions during the warm ENSO while the southern part is generally drier with the opposite taking place during La Nina.

The average rainfall for the Shire river basin is 888mm per year while the Ruo, receives an estimated 1300 mm of rainfall per year. The rainfall is highly regulated by altitude with the Mulanje Mountain playing an important role in the amount and intensity of rainfall. The rainfall within the Ruo basin varies spatially in terms of the amount of rainfall received and the intensity as well as the distribution of the rainfall events within the season. The variation in altitude is apparent with the lowest station located situated at a height of 52 meters above sea level and the highest station situated at 1146 meters above sea level.

Most of the hydrometric stations are not in good state and the 2015 floods damaged some of these too. This was expected to pose a challenge and uncertainties associated with data constraints which is common for most parts of Africa. Recent developments through the Shire River Basin Management Programme as well as the Modernised Climate Information and Early Warning Systems (M-CLIMES) have engaged in efforts to improve the spatial network of meteorological and hydrometric stations. The surface runoff for the Shire River basin is estimated at 580m^3/s and varies greatly with seasons given the very dry conditions associated with winters and early summer. The Ruo basin averages 81m^3/s annually with significant variations in the dry and wet seasons too. Inter-annual variability is also more pronounced with very low discharge and peak flows in dry years and the opposite for wet years.

As indicated in the Shire River Basin Atlas (GoM, 2016), the dominant land use is cropland and forests and grasslands in different states of degradation. Land use has changed over the years with most of the forested area (sparse and dense) being converted to cropland. Population growth is one of the major drivers of exploitation of land, forests among other natural resources. Malawi currently has the highest population density in Africa and is projected to grow even further with associated impacts on these natural resources. The rate of deforestation is one of the highest in the Southern African Development Community (SADC) and the world, mostly driven by demand for biomass energy and land for agricultural expansion and settlements. Changes in land use are not confined to the Shire River basin but rather widespread throughout the country. Figure 4.2 was derived from Food and Agriculture Organisation (FAO) data and highlights the general trend in the changes in the percentage of the total country area that is under cultivation-an increasing trend that has been particularly noted for the Shire River basin as highlighted in figure 4.9 in latter sections. Other land uses include dense and sparse forests and grassland (in different states of degradation) and built-up areas.

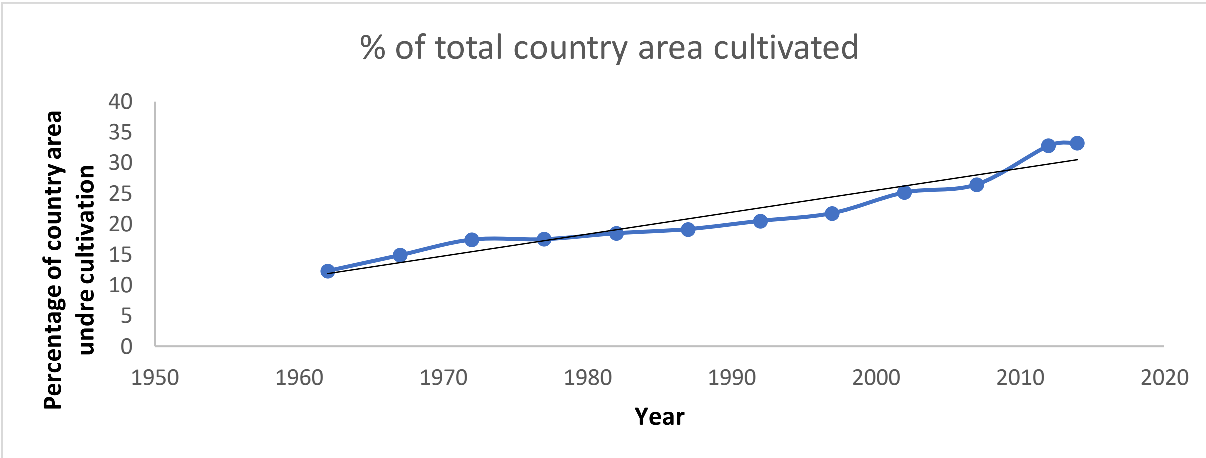


Figure 4.2 Long term change in the percentage of area under cultivation relative to country surface area (figure plotted with land use data for Malawi from FAOSTAT Database)

4.3 Characterisation of Rainfall during the 2015 Flood

Characterisation of rainfall during the 2015 event was based on data from four meteorological stations within the Ruo River basin. The four stations include Thyolo, Bvumbwe, Mimosa and Makhanga and are operated by the Department of Climate Change and Meteorological Services (DCCMS), details of which are provided in section 5.6 of the chapter 5 (Data and Methods). These analyses are not part of results hence they precede the results as well as (data and) methodology chapters to contextualise the event. The wet season for Malawi generally runs from November to April (some literature it may indicate October to April). Most of the rainfall is received between December and February. Seasonal anomalies were plotted to determine how wet the 2014/15 season was and whether it was wet enough to justify the fact the 2015 floods were the worst on record as claimed by the media and government reports. The anomalies were calculated by subtracting the annual or seasonal average from the climatological mean based on the four stations within the Ruo basin. When plotted in terms of anomalies, the 2014/15 season-during which the flood was experienced-does not indicate the most anomalously high seasonal or annual rainfall to justify that this was the worst floods on record. For comparison's sake, it was found that while the station dataset indicated rainfall above the climatological mean for the year 2015, the CHIRPS data indicated that the year received fewer rainfall. The same was found to be the case for the seasonal rainfall anomalies as depicted in figure 4.3.

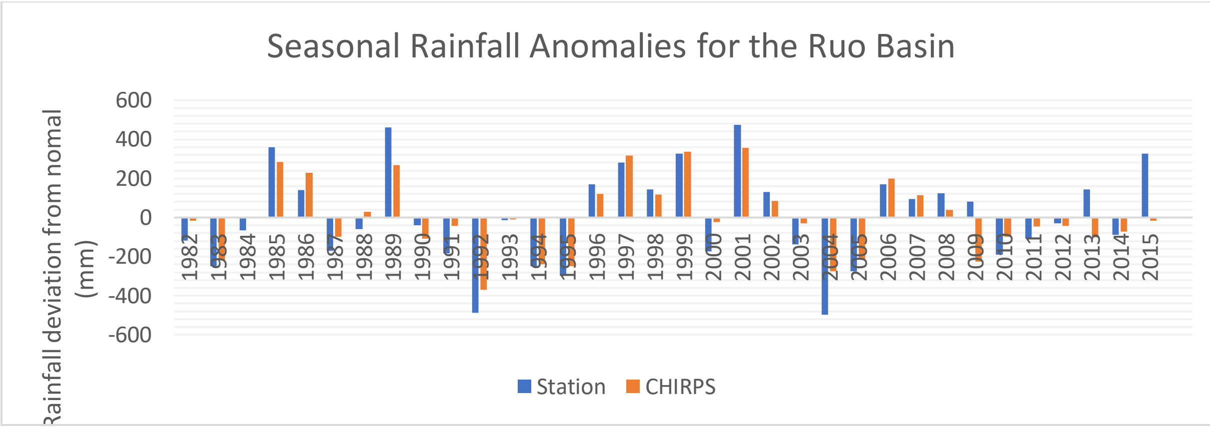


Figure 4.3 Seasonal rainfall anomalies for Ruo River Basin

Figure 4.3 suggests that the January 2015 flood event was not associated with an unusually anomalous wet season overall. It is likely, however, that is was a result of rainfall anomalies at shorter time scales. To explore that, anomalies of monthly, 5-day and 1-day rainfall were analysed. Analyses focusing on the shorter-term indices were reported based on the station data due to the CHIRPS Data's inability to capture higher extremes as given as will be discussed in section 6.2. The monthly timeseries in figure 4.4 is a four-station average of the total monthly rainfall for the entire series (1981-to 2015) for the months within the wet season. The extremity of the monthly rainfall for January 2015 is quite apparent from the timeseries and even more so when plotted for specific stations (not shown). The extremity of January 2015 rainfall was consistent across the three stations namely Bvumbwe, Mimosa, and Thyolo while Makhanga generally demonstrated no anomalously high monthly rainfall at any point during the season. Vanya (2015), highlights, in a case study for the same event, the rainfall variability with altitude noting that low lying areas received relatively fewer amounts of rainfall of rainfall as compared to high altitude areas which could be the case here given that Makhanga Station is located at a height of 52 meters above sea level.

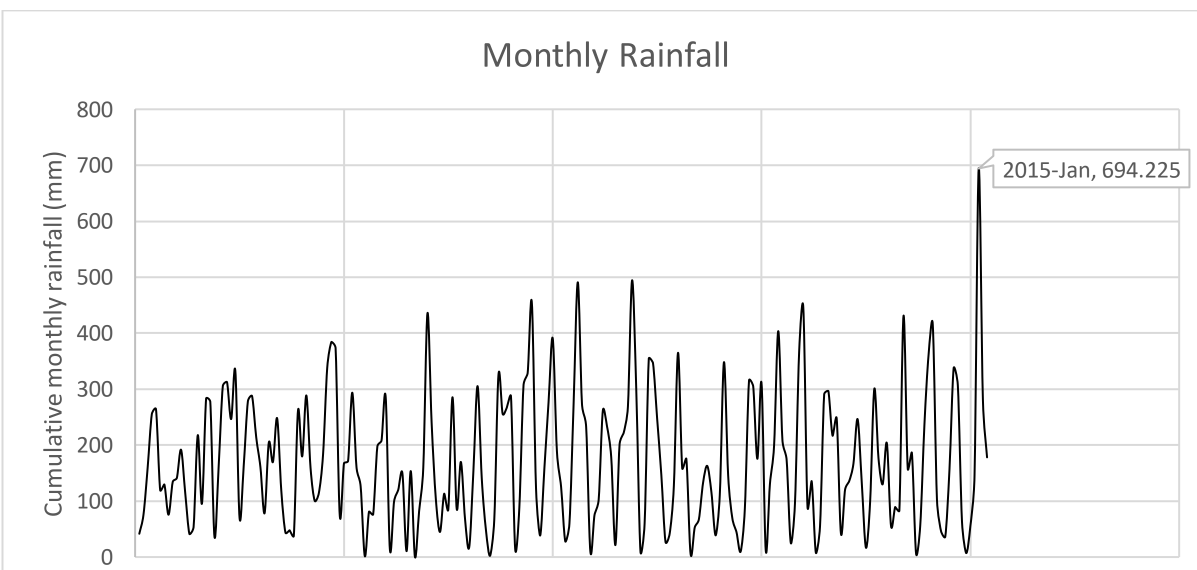


Figure 4.4 Timeseries for monthly rainfall within the rainfall season from 1981 to 2015 indicating the extremity of the monthly rainfall(4-station average) for January 2015 being higher than any other month before

A comparison of the climatological monthly rainfall averages against the monthly rainfall for the 2014/15 season indicated an anomalously high amount of rainfall in January 2015. The rest of the months in the 2014/15 season, however, had lower than normal rainfall-except for February as illustrated in figure 4.5. Monthly rainfall analyses had shown that it rains the most in January for a normal season with 28.7% of the rainfall received in that month. For the record, during the 2014/15 season, 51% of the rainfall was received in the month of January (with a considerably high volume as well). A record high during this month could be indicative of the nature of the extremity of the flood resulting from such extreme rainfall in the absence of streamflow data available to verify this and rainfall-runoff relationships in the years between 1900 and 2015. Such gaps in streamflow data are highlighted in latter sections.

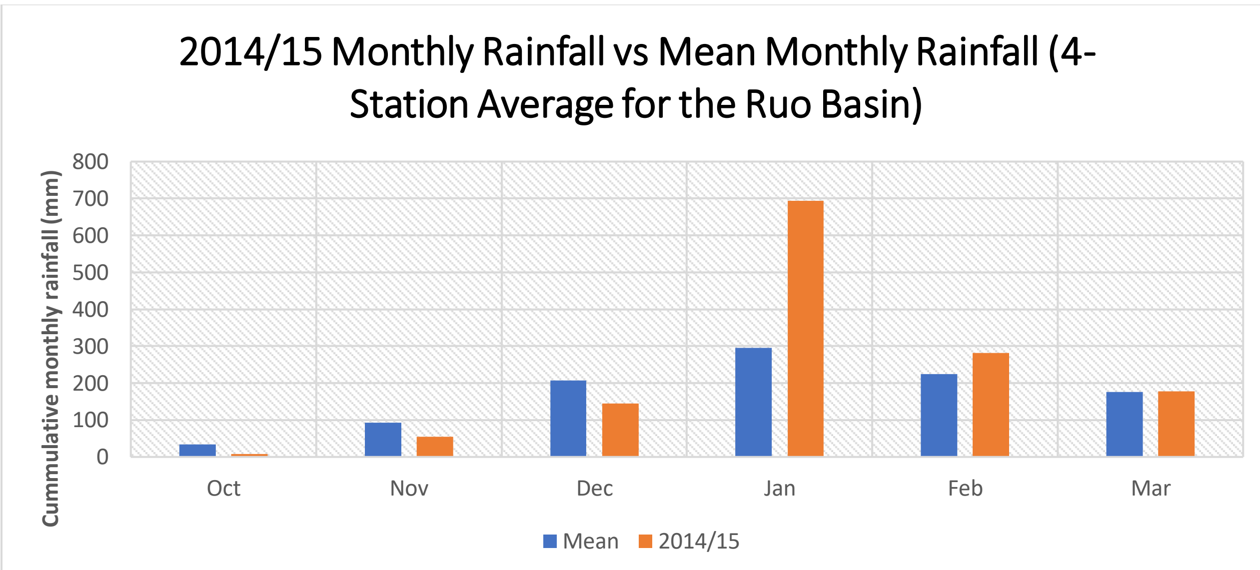
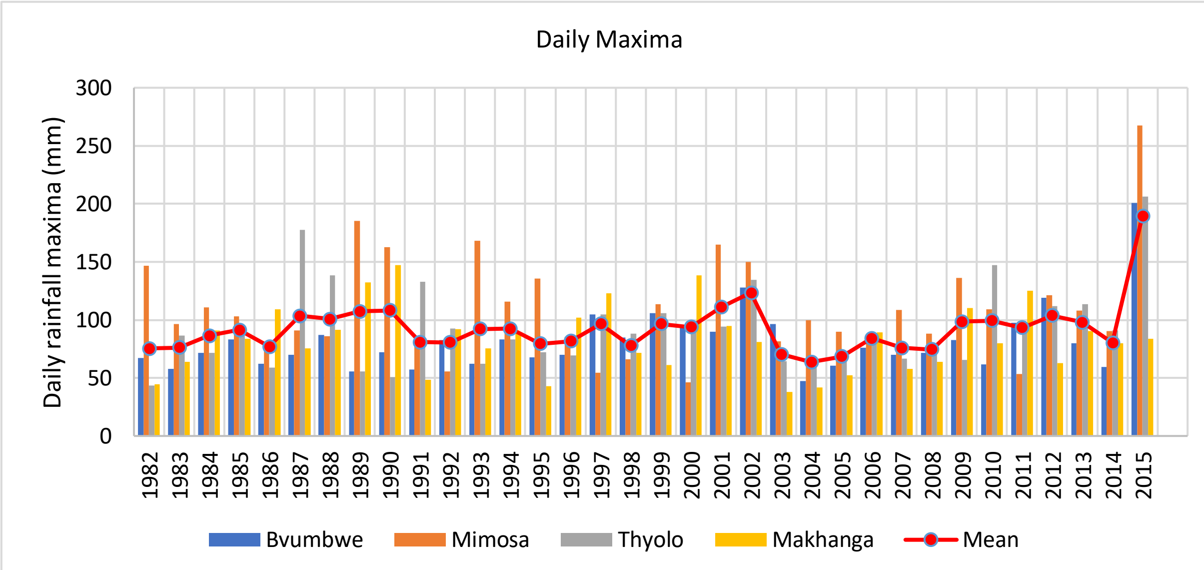


Figure 4.5 A comparison of the average mean monthly rainfall (4-station averages) and monthly rainfall during the 2014/15 season (4-station average)

One-day maxima and five-day maxima are some of the commonly used indices for analysing the extremity of rainfall and whether that is changing going into a warmer climate. Zhang *et al.*, (2013)and earlier Min *et al.*, (2011) used the 1-day and 5-day max indices for a detection and attribution study to determine whether rainfall was getting more intense with enhanced GHG forcing. In this study, five-day rainfall totals were derived from summing overlapping 5-consecutive days in each of the seasons under consideration. The five-day maximum for each season was derived from the five-day sums for that particular season. Both the 1-day and 5-day maxima were plotted for each of the 4 stations along with the arithmetic mean for the four stations. The rarity of the event in these indices for the 35-sason period could be noted from the time series given that, for both indices, the 2014/15 season had the highest daily maximum and five-day maximum for three of the four stations with the arithmetic mean reflecting the same pattern as illustrated in figures 4.6 a and 4.6 b. As a matter of fact, the three stations, namely Mimosa, Thyolo and Bvumbwe had the record highest daily rainfall recorded (the previous record daily rainfall records were 185.2 mm (in 1988), 177.3 mm (in 1986), and 192 mm (in 1967) respectively). Elsewhere in the stations within the Shire River basin, record daily rainfall volumes were reported in the 2014/15 season too. This highlights the extremity of the rainfall received and the potential severity with regards to extreme flooding too.

a



b

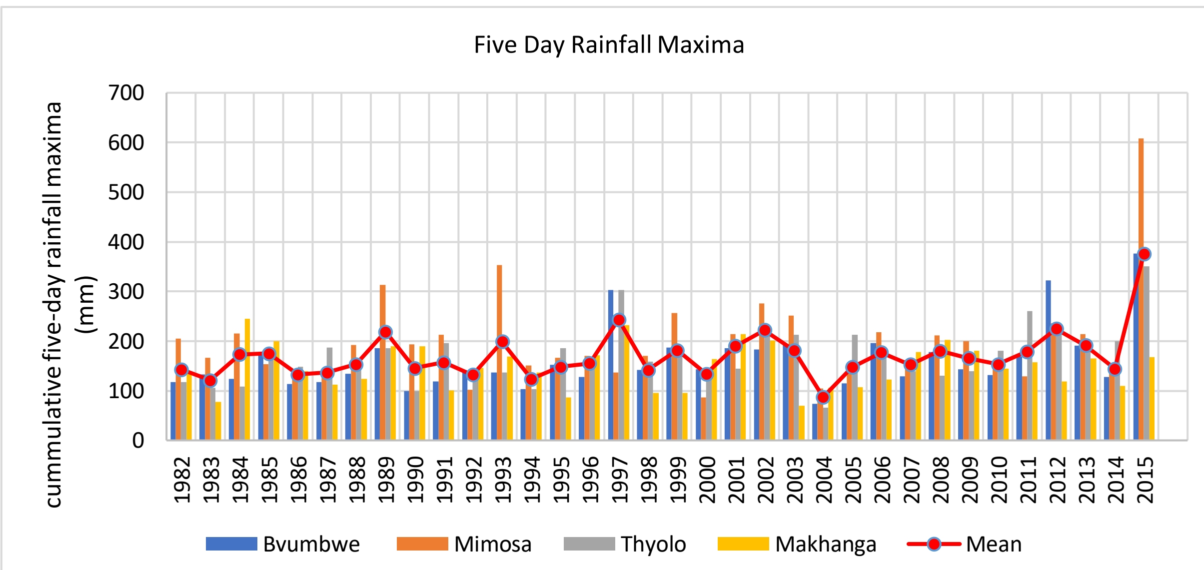


Figure 4.6 Daily Maximum (a) and 5-Day Maximum (b) rainfall for the four stations in the Ruo basin and their average

The extremity of the 1-day maxima and the 5-day maxima highlights the potential severity and the peculiarity of the events of the 2014/15 season. To complement the analysis of these indices, a wet day frequency analysis was done. A wet day is described in this case as a day in the season with 0.1 mm or more rainfall. The analyses were extended to explore the frequency of days with rainfall above 50mm, 100mm, and 150mm and this is highlighted in figure 4.7 a-d. An average season has 75 rainy days over the basin. The trend is however a declining one with the 2014/15 season only having 64 days of rainfall. If weighted against the amount of rainfall received in a season, it was established that while there is a decline in the number of rainy days, the amount of rainfall on rainy days is actually increasing. More intense rainfall may translate into an increasing risk of flooding. The frequency of days with rainfall above 50 mm highlights an increasing trend. This is consistent with what Vanya (2015) established in the context of the Shire River basin. The 50mm does not indicate extremity specific extremity for the 2014/15 case. However, higher order thresholds (100mm and 150 mm) indicate the rarity of the 2014/15 season with respect to such extreme events.

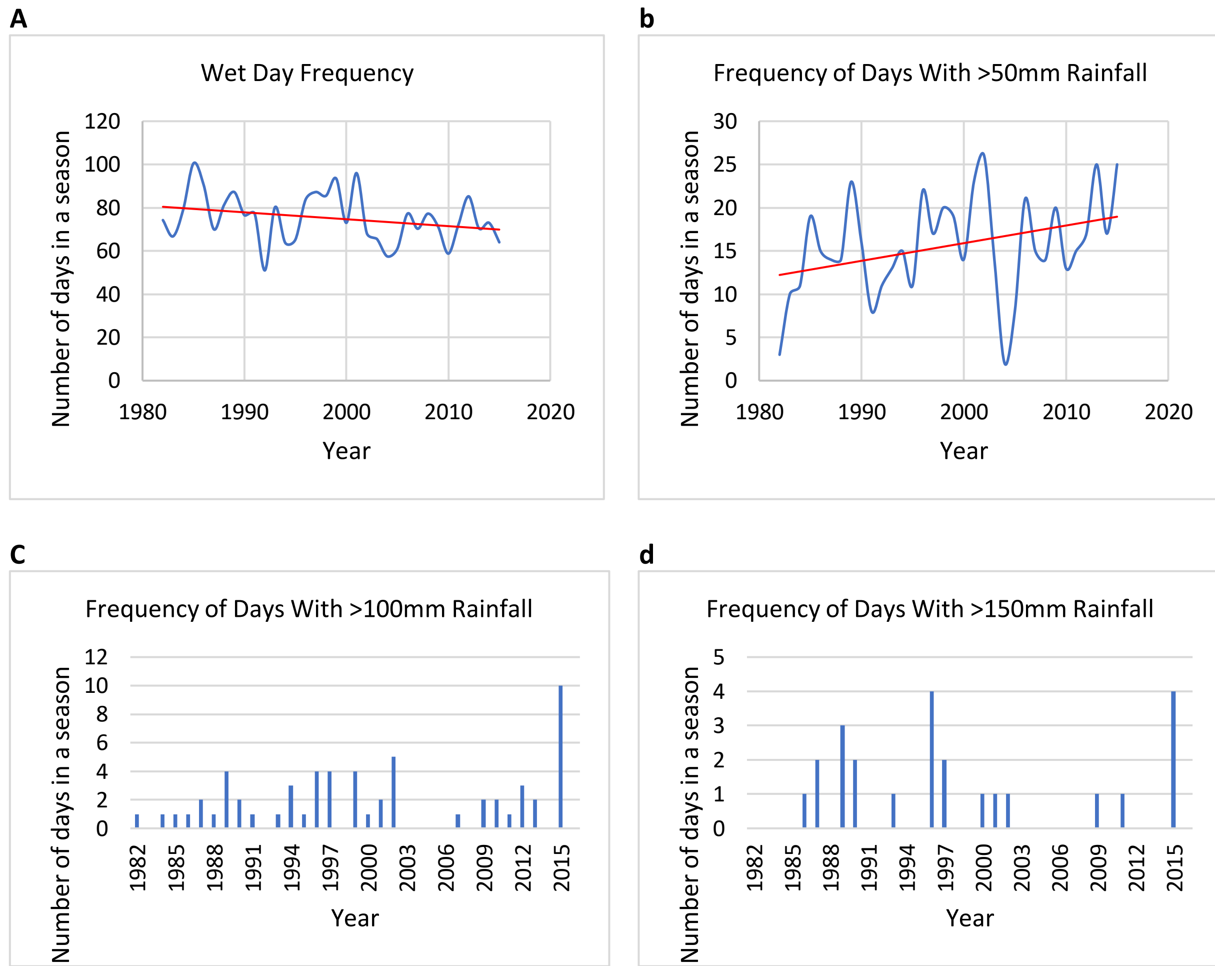


Figure 4.7 Frequency of wet days (days with average rainfall above 0.1mm), Frequency of events equal to or greater than 50mm (b), 100mm (c), and 150 mm (d)

4.3.1 The Driving Mechanisms for Heavy Precipitation during January 2015

It is fundamentally important to understand the nature of the extreme event from a meteorological point of view in order to understand the potential severity of the rainfall over the period of interest. This also creates a basis for the hypothesis attributing the extreme floods to climate change. The Department of Climate Change and Meteorological Services in Malawi periodically issues a 10-day weather and agrometeorological bulletin which reports on the weather for the previous 10 days and issues a forecast for the following 10 days. Its bulleting for 1st to 10th January 2015 underlined the nature of the extremity of the rainfall received over that period, with the same report forecasting that extreme weather conditions would prevail for the following 10 days (11th to 20th January 2015). Figure 4.8 is an excerpt from the weather bulletin highlighting the receipt of the flood-causing extreme rainfall and that more extreme rainfall would be received in an already flooded region for the ten days to come. It was reported in that bulletin that the driving mechanism for the extreme rainfall *was the combined effect of two rain-bearing systems namely the Congo Air Mass and an airmass from the Mozambique Channel*.

HIGHLIGHTS

- **Heavy rains caused floods in southern districts…**
- **Maize crop ranged from emergence to vegetative stages…**
- **Widespread heavy rains to continue during 11 to 20 January 2015…**

Figure 4.8 An excerpt from the DCCM's weather bulletin released on 10th January 2015 reporting on extreme rainfall that led to floods and forecasting more extreme rainfall in the days to come

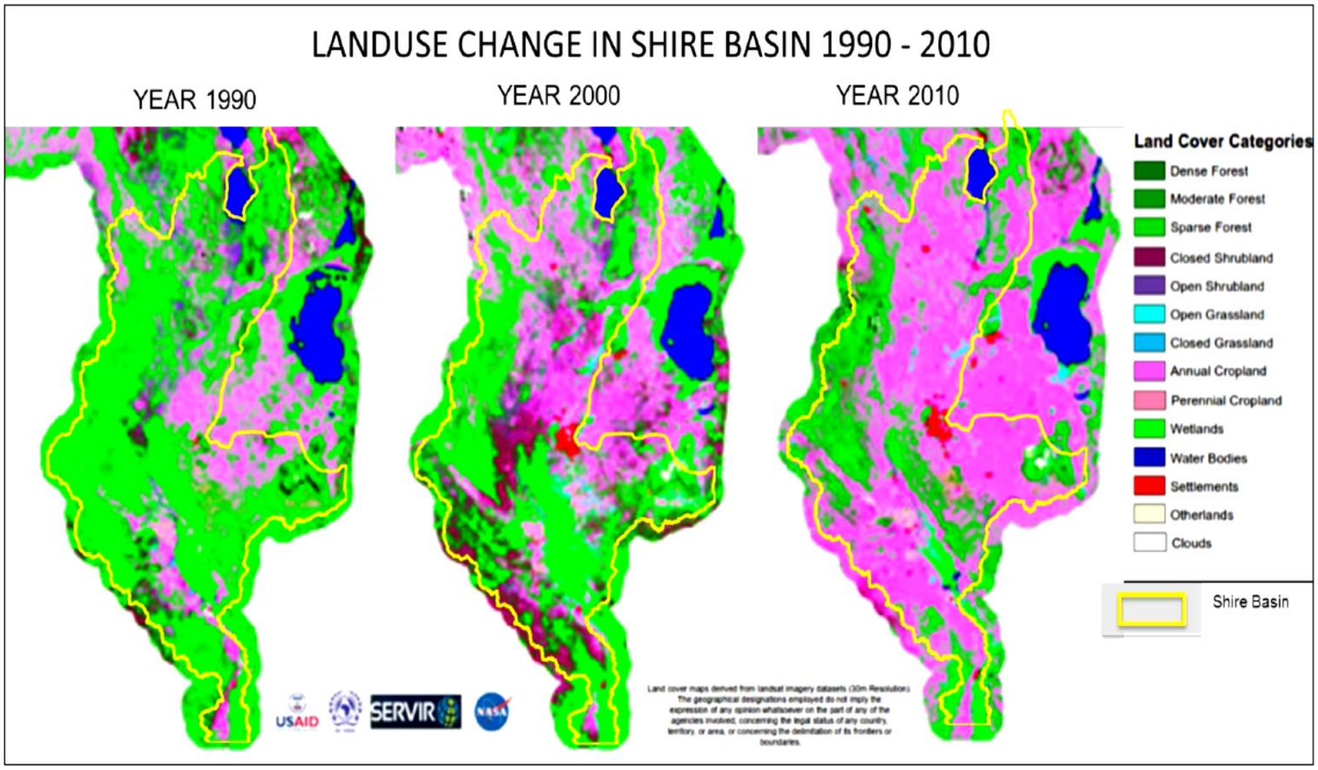
Most of the extreme precipitation had resulted from the tropical storm Chedza and the Tropical Cyclone Bansi, two phenomena that preceded each other in quick succession, dumping great amounts of moisture over the South-Eastern part of the continent. The extreme precipitation resulted in massive flooding in the countries like Malawi, Mozambique and Madagascar causing massive damage to property and loss of life. Rapolaki and Reason (2018) studied the tropical storm associated with the heavy precipitation that led to the flooding. While there have been fewer studies attempting to understand the tropical storms in the region, their findings provided a positive step for understanding the mechanisms associated with this and other tropical storms including circulation, winds, and rainfall. A similar study was also conducted by Vanya (2015) who looked at the influence of the Mozambique Channel on the extreme rainfall over the southern part of Malawi in January of 2015. Vanya (2015) focused his study onto the periods preceding the tropical storm Chedza as well as after the event.

Both Vanya (2015), and Rapolaki and Reason (2018) highlight the complexity of the dynamics that led to the extreme precipitation in January of 2015. Both studies however, provide a basis for understanding such extreme events from both a diagnostic point of view by understanding the evolution of such phenomena. Understanding the mechanisms (dynamics and thermodynamics) necessary for such events provides a good basis for understanding whether such events will change going into a warmer climate. In the same way, it also presents the opportunity to be able to evaluate models on the basis of their ability to simulate such events thus ascertaining whether they are fit for purpose not just for the simulation of the event but for attribution studies too. In addition, National Academies of Scinece Engineering and Medicine (2016) particularly underscore the fact that tropical cyclones and severe convective storms are related to large scale climate parameters whose relation to the events is understood to varying degrees, in general, and are more complex and less direct than changes in either temperature or water vapour alone. This study generally dwells on the end result of these meteorological events and their impact on hydrological process but underlines the relevance of explicitly studying these meteorological phenomena from an attribution point of view.

4.3.2 Accounting for the Role of Land Use and Land Cover Change in Modifying the Risk of Flooding

It is so often the case that during the occurrence of such events, climate change dominates the debate, yet there might be other factors that affect changing flood risk. The most obvious one for this particular basin is land use and land cover change. The transformation of the Shire River basin and its catchments has been well documented in a number of state reports and assessments while a few academic papers have been published on the same (GoM, 2010, 2016; Kambwiri *et al*., 2014). Deforestation has been rampant and the nationwide deforestation rate is the highest in the SADC region and among the highest in the world. Owing much to that is the demand for more land for agriculture-mainly crop production, settlements, and demand for charcoal and firewood which are the main sources of energy in the country. Specific to the Shire River basin, the Shire River Basin Atlas, published in 2016, highlights the changes in land use and cover in the basin for the period between 1990 and 2010 as illustrated in figure 4.9. There is a notable massive loss of forest cover and conversion of dense and sparse forests into crops lands-mostly arable. Such changes in land use and cover, coupled with a changing climate, may jointly influence the risk of flooding in the basin.

The realisation that land use and cover change could be exacerbating the risk of flooding in the river basin has seen notable investments in catchment management and land restoration projects in the river basin. However, other investments also seek to expand irrigation which may imply further land use changes that could increase the risk of flooding even higher if measures are not put in place. Understanding the change in the risk of flooding in the basin would therefore require that the most important risk factors are account for. From an attribution perspective, it would be essential not only to understand the risk of a particular flood event attributable to climate change but other risk factors which would not only contribute towards more confidence in the attribution but understanding of risk factors for better flood risk mitigation and proper loss and damage assessment too.



Source : Shire Basin extraction from http://rcmrd.org/wp-content/uploads/2014/06/malawi.png

Figure 4.9 Land use categories for three time slices indicating the state of land use by the years 1990, 2000, and 2010 (Adapted from the Shire River Basin Atlas, 2016)

4.4 Streamflow Based Event Definition

A risk-based event attribution considers a particular, well defined event. In this study, that event has so far been defined as the “January 2015 flood” and the extent of the damage, qualitatively reflecting its extremity, has been defined in chapter 1. In order to derive a quantitative description of the event’s risk and its change, that event needs to be appropriately defined too. The quantitative description of the event is generally based on observations during the occurrence of the event. When defining the event, the maximum value of the observations is often taken as the threshold or the magnitude for which the exceedance probability is determined for the different climate (and land use) scenarios. Given that the observed streamflow data were only available up to 1991, the event and indeed the threshold for which to determine the exceedance probability, was described based on runoff simulations based observed rainfall data. A detailed description of the model is given in the next chapter as is the detailed description of the modelling process. The assumption in this case was that the calibration of the model was representative for the entire period and that if station were available, the pattern would be consistent with that of the simulated runoff based on observed rainfall. Simulated daily discharge, corresponding to Ruo@ Sinoya South station, from 1981 to end of 2015 is shown in figure 4.10 which includes the station’s daily discharge over the period for which observations were available. Maximum annual daily peaks in the pseudo data were within the limit of the maximum in the available station data. However, the extremity of the 2015 event was notably anomalously higher (6950 m^3/s) than any other peak events in the preceding years.

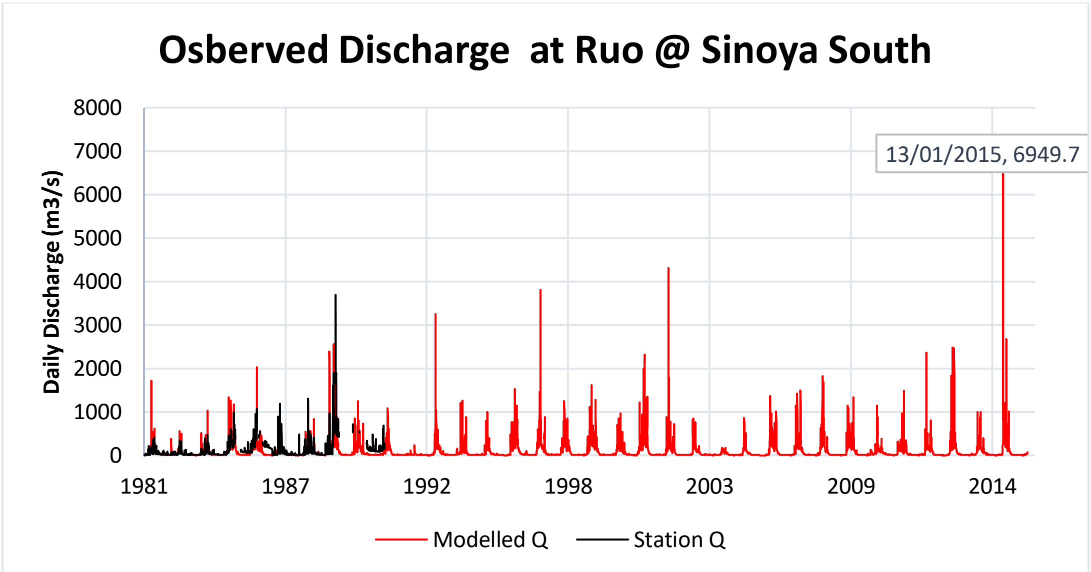


Figure 4.10 Daily discharge indicating anomalously high discharge in January 2015

Due to lack of precise hydrological data with which to precisely define the event in terms of time and location, two other metrics, namely 10-day flows and 30-day flow were also used. The 10-day and 30-day maxima were derived from the running averages of the daily discharge at 10-day and 30-day intervals respectively. Consideration of different temporal metrics was also based on size of the catchment being analysed and the associated difficulty of precisely determining the temporal scale of the event. A similar nature of extremity was noted for the 10-day and 30-day (figure 4.11) average stream flows such that flows in January 2015 were highest on record for all the three durations considered. Comparisons with the stations for the 10-day and 30-day running means would not be applicable to an extent given the gaps in observations which could lead to misrepresentation of the running means hence making them not comparable to a more continuous dataset based on the simulated discharge.

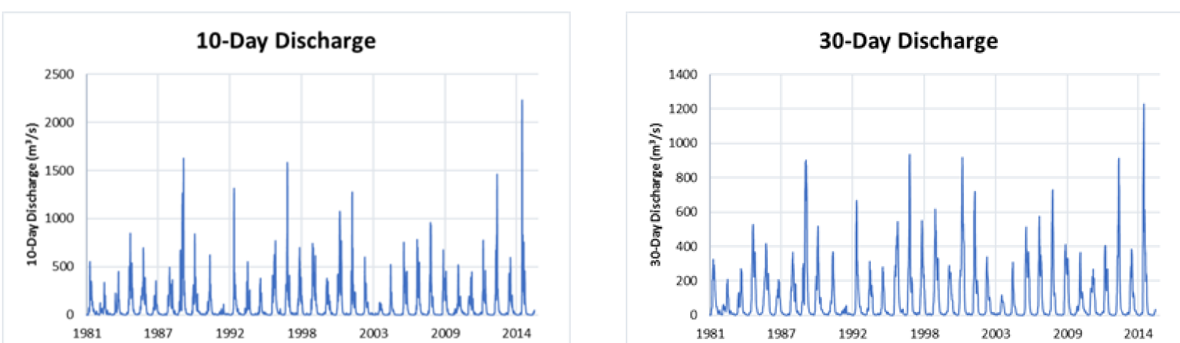


Figure 4.11 10-Day and 30-Day discharge indicating anomalously high discharge in 2015

The attribution process was based on the maximum values for the observed discharge for the three durations such that the analyses would be aimed at determining the probability of exceeding a daily peak, 10-day maximum or 30-day maximum in the streamflow timeseries for a particular climate-land use scenario. Table 4.1 summarises the thresholds for which the exceedance probabilities were determined for the 1-day, 10-day and 30-day events based on the maximum observed value for each metric during the occurrence of the event which, in this case, was also the maximum for the record within the period under consideration.

Table 4.1 Thresholds for which exceedance probabilities were determined for the 1-day, 10-day and 30-day metrics

Metric	Threshold (m^3/s)
1-Day Max	6950
10-Day Max	2233
30-Day Max	1226

5 Data and Methods

This chapter highlights experimental setup for both the climate and hydrological modelling components as well as the general framework relating them. It also highlights the data sources and the analysis of the results to determine the Fraction of Attributable Risk as well as analyses to highlight the challenges associated with data issues as highlighted in the introduction and in line with the second specific objective. The approach for conducting the study draws from existing and well documented procedures for modelling extreme events as well as probabilistic attribution procedure based on the concept of FAR. The basic approach has been reflected upon in the literature concepts chapter, but this chapter extends further to provide a detailed description of how these approaches were applied for this specific study.

5.1 Conceptualising the Experiment

The study was based on the concept of fraction of attributable risk-the key concept underlying the risk-based approach in probabilistic event attribution. In the context of this study, the approach was used to determine how the probability of exceeding peak stream flows experienced in 2015 (at 1-day, 10-day, and 30-day durations) varies in "factual" and "counter-factual" climates and in different land use and land cover scenarios. By analysing the differences in the exceedance probabilities in the two climate states, it would be possible to determine the fraction of the risk that is attributable to climate change due to anthropogenic greenhouse gas emissions. The conceptualisation and setting up of the experiment had to be consistent with the framing of the attribution question which, in this case, was to determine how the likelihood of experiencing a flood of the January 2015 magnitude changes as a result of anthropogenic emissions against a background of changing land use and cover. Flood risk analysis may focus on metrics or features such as stream flow, area under inundation, and damage caused. In this study, however, the analysis was limited to stream flow, specifically 1-day, 10-day and 30-day maximum flows, given data availability, model capability, as well as the level of complexity which the analyses of those other feature demands.

The study attempted to answer the question of how two external factors-climate change and land use and land cover change-might have, exclusively or jointly, influenced the risk of experiencing the 2015 floods. In order, to achieve this, a hydrological model was run with precipitation from two different sets of climate model ensemble simulations. The first set is the "factual" climate simulation where the climate model is forced with both natural and anthropogenic emissions of greenhouse gases consistent with observations of the atmospheric conditions as at the time of the occurrence of the event while the other is a hypothesised "counter-factual" case where the model is forced with emissions from natural sources only to mimic a climatic state without anthropogenic influences from greenhouse gas emissions. In the subsequent sections of this report, the outputs from the "counter-factual" and "factual" climate model simulations used to drive the hydrological model may be collectively referred to as "attribution data". The hydrological model was forced with the attribution data in order to determine how runoff varies in the factual and counter-factual climates.

To account for the impact of land use and land cover change, the hydrological model would be conditioned on land use characteristics. Two land use scenarios were identified based on the land use and cover mapping of the catchment as well as land use data available from sources described later. The first land use scenario (historical) was based on the land use and cover in 1990 and the second scenario (current) was based on the 2010 land use and cover in the catchment in which case it was assumed that that land characteristics during the time of occurrence of the event closely resembled the land characteristics in 2010.

Each climate-based simulation would therefore be replicated once but with altered land characteristics in the hydrological model. Thus, a total of four sets of experiments would be conducted, in which the two climate-scenario based simulations were repeated for the two land use scenarios. The first set was a combination of the counter-factual simulation conditioned by historical land use which offered as a control. The second set was a combination of the counter-factual climate scenario and historical land use in order to test the effect of land use alone. The third set was a combination of the factual-climate scenario and historical land use which would test the how the risk of flooding varies with climate in the event that land characteristics had remained as they were in 1990. The fourth set would offer and understanding of how the risk of flooding varies as a function of both land use and cover change and climate change from anthropogenic influences.

The process is summarised in the illustration in figure 5.1. The key output from each simulation was the discharge or run-off as a function of the input data and the land characteristics on which the simulation was conditioned. The experiment yielded a total of four sets of outputs from which probability density functions of discharge under different climate and land use scenarios were derived for the daily run-off outputted from the model simulations. The threshold was set based on the annual peak run-off for the 2014/15 season. For purposes of this study, the threshold will be referred to as Q2015. The PDFs fitted to the data were used to determine the exceedance probability of Q2015 for sets of simulations. The fraction of attributable risk was determined by comparing the differences in the exceedance probabilities of the three experiments against the control.

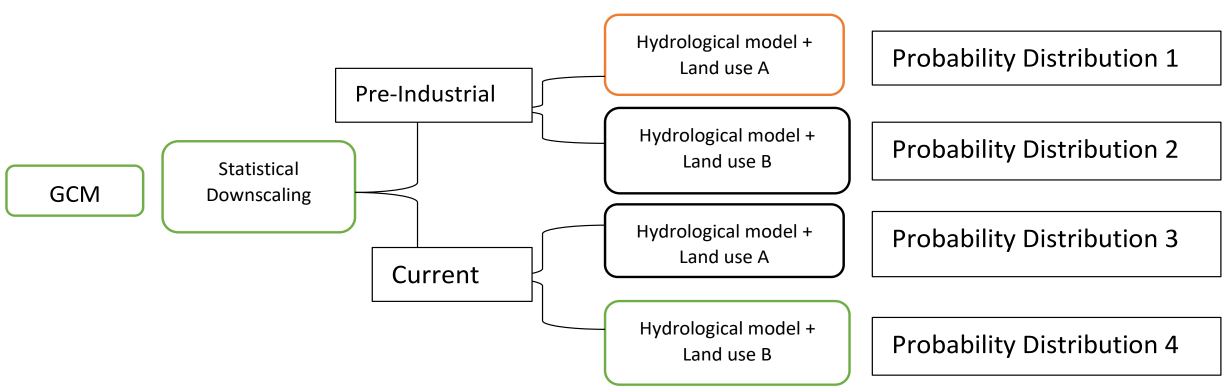


Figure 5.1 Framework summarising the experimental set up

From a risk perspective, there are two fundamental functions to determine the change in the risk and to determine how much of that change is attributable to climate change as a result of anthropogenic emission of greenhouse gases or land use and cover change or a change in both factors. The probability ratio (PR) is used to determine the change in the risk or probability of occurrence of an extreme event and this is expressed as $PR=P_1/P_0$ where P_1 and P_0 are the exceedance probabilities of the extreme event in the factual and counter-factual climates respectively. The fraction of attributable risk (FAR) is used to determine the proportion of the risk attributable to anthropogenic global warming and is expressed as $FAR= (1-P_0/P_1)$. Given that this study had three experimental scenarios and a control, PR and FAR were determined for the exceedance probability for a flood of Q2015 magnitude from the probability distributions for each of the three experimental scenarios, relative to the probability distribution of the control, expressed as P_a, P_b and P_c for scenarios a, b and c respectively. With P_0 denoting the exceedance probability for a flood of the Q2015 magnitude in the control scenario, the FARs for the three sets of scenarios were derived based on the probability relationships summarised in table in table 5.1. The detailed application of this conceptualisation in determining the FAR from the simulation outputs of this study is highlighted in section 5.8 of this chapter.

Table 5.1 Summary of experimental scenarios and their corresponding FAR calculation in relation to the control

	Description	Probability Ratio	Fraction of Attributable Risk
Control	Counterfactual climate x Historical land use. In the context of this study this is the designated control against which the other scenarios ('treatments') are evaluated for probability ratio and FAR. The exceedance probability for a Q2015 flood for the control is denoted as P_0		
Scenario A	Counterfactual climate x current land use. The exceedance probability for a Q2015 flood for this scenario is denoted as P_a.	P_a/P_0	$1-(P_0/P_a)$
Scenario B	Factual climate x historical land use. The exceedance probability for a Q2015 flood for this scenario is denoted as P_b.	P_b/P_0	$1-(P_0/P_b)$
Scenario C	Factual climate x current land use. The exceedance probability for a Q2015 flood for this scenario is denoted P_c.	P_c/P_0	$1-(P_0/P_c)$

5.2 Description of the Climate Model and Attribution Data

The hydrological model was forced with attribution data from HadAM3p "factual" and "counter-factual" simulations. The HadAM3p is an atmospheric global climate model of the atmosphere and land surface only with SST, greenhouse gas concentrations and other conditions imposed on the model. The model is run at N96 resolution (1.25 by 1.875 degrees, 19 levels: 192 grid boxes in the longitude and 145 grid boxes in the latitude; representing 208km x 139 km at the equator) with 15-minute timesteps for dynamics and improved physics. It is a UK Met office model and has been widely used in attribution experiments and it is the standard for "weather@home" experiments in the climateprediction.net project (see https://www.climateprediction.net/). Since 2010, the model has been used by the Climate Systems Analysis Group (CSAG) as the basis for weather risk attribution forecast replacing the HadAM3 (run at N48 resolution) which had been used since CSAG started issuing seasonal forecasts in 2002. Wolski et al

(2014) used results attribution data generated from the same model to drive the hydrological model for risk-based extreme event attribution.

The setup of the climate model and the linking up with the hydrological model follows the same approach use by Wolski *et al.* (2014). The model is run based on a seasonal forecasting framework "time slice" approach described in full detail in Stone et al (2014). It is an alternative experimental set up to century-long simulations of coupled models at a lower resolution. Reproducing extreme events may be difficult in the coupled model century-long experimental setup. In this case, therefore, a trade-off was made between applicability of experimental setup and climate model setup such that the experimental setup was a more desirable and feasible criterion over the climate model setup. Under this framework, the simulation of atmospheric weather pays attention particularly towards surface boundary conditions rather than their origin in which case a short spin up, enough to explore the bulk of the weather attractors sufficient for many extreme events of interests would be applicable. This is an important element of the experimental setup as such it is an important qualification to consider when interpreting the results of the modelling under such a framework. Nonetheless, interpretation must concede that "stricter" experimental setup is consistent with the improvements in coupled ocean-atmosphere models as well as feasibility in computing capabilities.

As highlighted, in section 4.3.1, the extreme precipitation leading to the flooding in 2015 was as a result of tropical cyclone Bansi and tropical storm Chedza both of which may not be realistically simulated by the HadAM3p model with the possibility of some runs not even reproducing such cyclones or depressions. Being mainly exploratory in nature, the study largely focused on integrating climate attribution simulations into the process of joint attribution of impacts in an African context where climate data are sparse too. In this view, the fitness of the model to simulate the actual meteorological phenomena leading to the extreme precipitation that caused the floods of interest to the study is not of primary importance to the study. With not too many models run in attribution mode that can actually, realistically simulate tropical depressions and cyclones, the model HadAMP3P and the context in which it is run, provided a feasible option to explore the research questions at hand.

For this experiment, the model was run specifically to generate simulations of the 2015 climate under two different emission scenarios; the factual and counter-factual. In doing so, a seasonal forecast is generated for the current climate in the factual mode while the counter-factual generates a seasonal forecast as it would have been had there been no influence of greenhouse gases on the climate system. When simulating the factual mode, the model is driven by observed monthly sea surface temperature, annually varying CO_2 concentration while vegetation is fixed. The simulation also includes climatological seasonal variations in sea ice coverage. In the counterfactual mode, the greenhouse gas concentration is fixed to preindustrial times. The same observed monthly sea surface temperatures are imposed on the model but taking into account that the observed SSTs are in the context of a climate subjected to global warming from the greenhouse effect. The SST warming attributable to the GHG effect is therefore removed from the observed monthly SSTs. The warming attributable to greenhouse gas emissions (that which is removed from the SST for the counter-factual simulation) is estimated using an optimal total least squares regression analysis. This analysis is performed on data from the HadSST2 dataset of gridded observational measurements; and outputs from simulations of the HadCM3 coupled ocean-atmosphere climate model. The limitations constraints as well as the trade off and rationale for choice of approaches to this analysis are described in full detail in Stone et al (2015). The initial conditions ensemble approach was employed in this study with each mode (factual or counterfactual) run 20 times with perturbed initial conditions for each run. A total of 40 runs, 20 for each mode (i.e factual and counterfactual), were realised with each run downscaled 10 times following the procedure described in section 5.3 below. Thus the climate simulation and downscaling processes obtained a total of 400 realisations (200) used to drive the hydrological model.

5.3 Downscaling the Climate Model Outputs

When linking the climate model to the hydrological model via the meteorological variables outputted by the climate model, it is necessary to verify that the chosen climate model, when forced with the external forcings as we know them, should be able to reproduce the climate as has been observed. Downscaling to the smallest feasible spatial scale is an essential process for the modelling and analysis of climate change and its impacts amongst the impact community. To achieve this, dynamical and empirical downscaling procedures are used. The former uses regional climate models (RCMs) while the latter generally employ statistical models with transfer functions based on transfer function derived from observe and modelled climate parameter relations. In some instance, bias correction is used to correct any systematic biases in the modelled climate in relation to the observed climatology. Several empirical downscaling procedures exist, and some studies have been done to assess the reliability of each procedure with each procedure having its own limitation and gains based on the application and region among other factors. This study used the Self Organising Maps (SOM) procedure (Hewitson & Crane, 2006), developed and used at CSAG. The downscaling was not carried out within the work described here, but instead, the results of routine downscaling of HadAM3p attribution simulations available from CSAG were used (P. Wolski, 2018, pers. comm.). The downscaling procedure is briefly described below.

A self-organizing map (SOM) is a data description and visualization tool that extracts and displays the major characteristics of the multidimensional data distribution function. SOMs are typically depicted as a two-dimensional array of nodes (although other topologies are possible), where each node is described by a vector representing the mean of the surrounding points in the multidimensional data space.

In the SOM-based downscaling procedure, SOM methodology is used to identify "classes" of synoptic circulation over the location of interest. The variables used to define synoptic circulation include wind fields at 700mb derived from reanalysis (ERA-Int) data. Classes of synoptic circulation are identified on daily basis. An empirical cumulative distribution function (ECDF) of daily rainfall is then determined for each of the classes based on observed rainfall at a particular downscaling target. Subsequently, daily synoptic fields from HadAM3p model simulations are "mapped" onto the SOM classes, and rainfall values are randomly drawn from the ECDF corresponding to each of the classes. This allows for generating of time series of daily rainfall that is conditioned on the atmospheric circulation simulated by HadAM3p under a particular experiment. The procedure is repeated to create a number of time series of stochastic character.

Daily rainfall data from the four meteorological stations within the catchment, available from 1981 were used to train the downscaling. Each of the 40 (20 for each forcing mode) simulations was downscaled 10 times thus realising 400 outputs, 200 for each mode; i.e. factual and counterfactual. The hydrological model used in this study runs on a daily time-step as such the downscaled daily rainfall was not aggregated to longer timescales such as monthly as might be the case with some other similar studies where the hydrological model runs on a different time-step as the attribution data which to force it.

5.4 Description of the Hydrological Model

There are no prescribed criteria for choosing a hydrological model as every study has its own rationale for the choice model. However, Beven (2012) highlights the following important steps to consider when choosing which model to use in a hydrological modelling study;

1. Prepare a list of models under consideration including both those that are readily available and those one is ready to consider bearing in mind the monetary and time investments
2. Prepare a list of variables predicted by each model and those required for the purpose of the study in which case one seeks to determine whether the model under consideration is adequate to give them the variables they seek to predict.
3. Make a list of assumptions in the model. It is likely that for all models, the assumptions will be limiting in terms of what is known of the catchment's response. As such this assessment is relative and just a screen to reject those models that are based on the incorrect representations of the catchment processes.
4. Determine the inputs required for the model for flow domain, specification of boundary/initial conditions, and for the specification of parameter values.
5. If no model is left at this stage repeat 3-5 but more relaxed on the specific details.

The Swedish developed *Hydrologiska Byrans Vattenbalans-avdelning* (HBV) model was used for the rainfall-runoff simulations on the basis of the experimental set up described earlier in section 5.1. The model was developed by the Swedish Meteorological and Hydrological Institute (SMHI) for Scandinavian catchments but has been successfully applied in over 38 countries. The model provided a plausible option among a range of models and was specifically chosen for this study given that it is not computationally demanding and easy to set up coupled with the fact that its design is favourable to address the research questions explored in this study.

The HBV model is a conceptual, semi-distributed model. Semi-distributed in the sense that the basin can be subdivided into smaller sub-basins and each sub-basin further divided into elevation and vegetation zones. The model therefore allows for the partitioning of the catchment into different sub-catchment on the basis of the different characteristics influencing rainfall-runoff relationships. The sub-catchments are further divided into elevation zones depending on the heterogeneity of the elevation characteristics of the catchment. Each elevation zone is then further divided into vegetation zones to reflect on the heterogeneity of the vegetation characteristics. It is possible to characterise the land categories into three classes as "field", "forest", or "glacier". Figure 5.2 is a schematic of the HBV model set up highlighting the different processes from precipitation (as snowfall and/or rainfall) to discharge. The model has four routines; the snow/rainfall routine, the soil moisture routine, the response routine and the transformation routine.

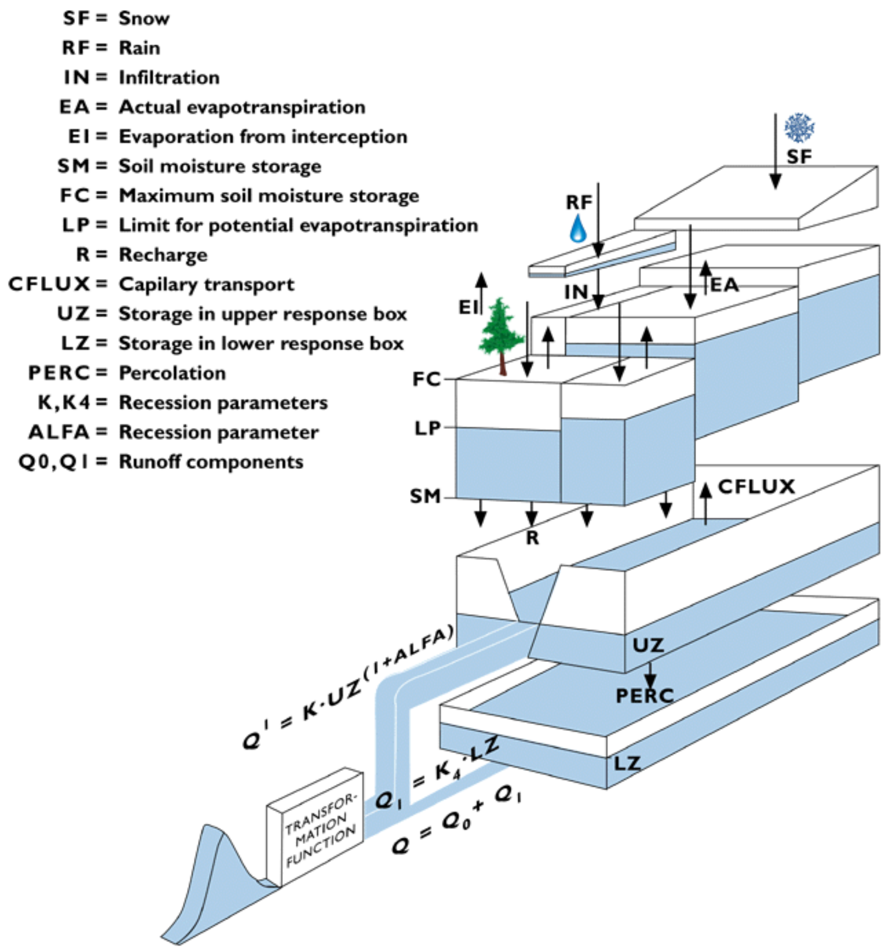


Figure 5.2 Schematic of the HBV Model (Image sourced from Macauley Land Research Institute (http://macaulay.webarchive.hutton.ac.uk/hydalp/private/demonstrator_v2.0/models/hbv.html))

5.4.1 Snow/Rainfall Routine

The snowfall routine is based on a simple degree-day relation in which case a threshold temperature is specified above which snowmelt (where applicable) occurs. The same threshold is used to determine whether precipitation occurs as snowfall or rainfall in which case the latter was applicable for the basin in this study as all precipitation occurs as rainfall. Glacial melt is also handled in the same routine. However, glacial and snow melt as well as snow fall were not applicable in the context of the basin as such the routine was only used to emphasise that precipitation falls as rainfall in the basin.

5.4.2 Soil Moisture Routine

The soil routine controls the runoff formation and is mainly based on three parameters **Lp**, **B (Beta)**, and **FC** where **Lp** is the limit of soil moisture content at, or above which, potential evapotranspiration takes place. **FC** is the maximum soil moisture in the model and **B** is the parameter that controls the contribution to the response function (Q/P; i.e. the runoff coefficient-the proportion of the rainfall forming rainfall) or the increase in soil moisture from each millimetre of rainfall. The soil routine works in such a way that the run-off increases with increasing soil moisture with actual evapotranspiration also increasing with increasing soil moisture and reducing as the soil dries out. Evaporation correction factors, both general and specific for forest and lake zones also control the soil routine in which case the long term mean values for evapotranspiration are used with a factor controlling interannual variability. The parameter **Lp** is expressed as a fraction of the parameter **FC**. The parameters values for this specific experiment are given in section 5.7 under calibration and validation along with the parameter values for the other subroutines.

5.4.3 Response Routine

The response or run-off generation routine transforms excess water in the soil moisture zone into runoff. The function has one upper non-linear and one lower linear reservoir from which quick and slow runoff components of the hydrograph originate respectively. The effective precipitation is added to the upper reservoir and with the control of the parameter, **PERC**, whenever this reservoir is filled with water, the excess water percolates to the lower reservoir. When the effective precipitation (or the yield) is high then percolation is not enough to relieve the upper reservoir of its moisture such that the upper reservoir directly contributes to the discharge that is generated through the more superficial channels. The lower reservoir represents the catchment's ground water storage contributing to the base flow. In some instances, reservoirs can be added between the upper and lower reservoirs to account for the differences in the soil moisture and recession in discharge transformation within the soil profile. The outflow from the upper reservoir is given by the formula;

$$Q_0=[K*UZ]^{(1+alfa)}$$

Where Q_0 is the reservoir outflow for the upper response box

K is the recession coefficient for the upper response box

$\mathbf{UZ_1}$ is the reservoir content and

Alfa is the non-linearity parameter

The model derives the parameter **K** from the relationship between **hq**, **khq** and $\mathbf{UZ_{hq}}$ where **hq** is the high flow level at which the recession rate **khq** is assumed and $\mathbf{UZ_{hq}}$ is the reservoir content at which the high flow level is assumed. The three variables are related by the expression $hq=khq*UZ_{hq}$. The flow represented by **hq** is the flow from the response box and not the flow after routing through the river and lake system. The linear flow in the response box is given by the expression $Q_l=K4*LZ$ where **LZ** is the reservoir content in the lower response box, **K4** is the recession coefficient in the lower response box and $\mathbf{Q_l}$ is the linear outflow in the lower response box. Where extra response boxes are added between the upper and lower response boxes, parameters k0-k3 and uzl0-uzl2 are used to represent the reservoir outflows and recession coefficients for the corresponding response boxes respectively.

5.4.4 Transformation Routine

To get a proper hydrograph shape at the catchment outlet, the runoff generated from the response routine has to be routed through the channel by a transformation function. As described in the IHMS manual, the transformation function is a simple filter technique with a triangular distribution of the weights. The parameter **Maxbaz** controls the time base of the triangular distribution and is used in all new calibrations as it is independent of timestep. The parameters **damp** and **lag** are used in relation to the transformation functions to sum runoff from interconnected sub-basins. These parameters control the inflow from other sub-basins which is added to the local runoff computed by the model and assumed to be entering the basin through a river channel from the outlet of the upstream sub-basin to the current basin. A modified version of *Muskingum's* equation is used to compute the delay of the flow of water in a river channel using the parameters **lag** and **damp**. The parameter **lag** is used to subdivide the river channel into a number of segments and is calculated as distance/velocity while the parameter **damp** describes the attenuation of the hydrograph through a river. Other supplementary functions controlling abstraction, bifurcation, lakes and transmission losses through the river channel which were not used in this experiment given the characteristics of the catchment.

5.5 Setting Up the Model District

The first stage in setting up the HBV model is to create a district which represents the main catchment and its characteristics including the stations and data with which to run the model. A district has the main basin and the different sub-basin making up the catchment. Each sub basin is further divided into elevation and vegetation zones each assigned a value representing the proportion of the area of the sub-basin that it takes or simply the surface area in km^2. Model parameters are specified for each sub-basin with universal parameters assigned to the main basin. Two vegetation characterisations were used to represent the historical land use and cover i.e. the land use and cover in 1990 and the land use and cover at the time of the occurrence of the flood.

Therefore, two identical districts were set up and differentiated in terms of land characterisation. The districts were set up to closely resemble the Ruo Catchment as closely as possible in terms of elevation, vegetation, and other characteristics controlling rainfall-runoff relationships. Like the Ruo catchment, each district had an area of approximately 4,600km^2 and into three sub-basins namely Ruo_main, Thuchira, and Luchenza. Each subbasin was further divided into elevation zones and each elevation zone further subdivided into vegetation zones as per land use characteristics for the two points in time considered in the study. The calibration of the model was done on the basis of the historical land use as it was the same period for which calibration and validation data were consistently available. All other parameters were kept constant to ensure that differences were only attributed to changes in land use characteristics. The land use options in the HBV model include forest, field (cropland), lake, glacier. Only "forest" and "field" categories were applicable in this study and these were changed accordingly in the two districts to reflect the different states of land use represented by each district set up.

5.6 Data

Various datasets were required for the study. While the model was forced with attribution data from the climate model simulations, rainfall and temperature data were required for the calibration and validation of the hydrological model, downscaling (bias collection) of the precipitation and temperature from the climate model simulations as well as the characterisation of the event. Run-off or discharge data were required for the calibration and validation of the model as well as the characterisation of the event.

5.6.1 Rainfall and Temperature Data

Rainfall and temperature data were obtained from the Department of Climate Change and Meteorological Services (DCCMS). Daily rainfall from 1st January 1981 was provided for 23 stations in the Shire River Basin out of which four stations fell within the Ruo Basin. The daily rainfall data provided had no missing values and, as a prerequisite, homogeneity tests were done within the HBV model environment prior to the calibration and validation preceding the simulations. An elevation correction factor in the HBV model correct the precipitation based on the elevation of region in a relation to the elevation of the station. Supplementary rainfall data from the Climate Hazard Group Infrared Precipitation with Stations (CHIRPS) were also used. CHIRPS is a satellite based global precipitation dataset are available from 1981 to date at 5 kilometre resolution. Data for points corresponding to each of the 4 stations were extracted and complied into a time-series corresponding to the time-series of the station data. This was compared to the station data for quality control and to determine which data best-represented the rainfall for the basin and most importantly the extreme event in January of 2015. In the context of the second objective, the two datasets were explored for various indices to determine the usability of available observed rainfall data for probabilistic event attribution in the region given that observational challenges are a key constraint for climate studies in the region. Temperature data were available for three stations within the Ruo basin with temperature records from the 1st January 1981 for two stations and 1st January 1987 for one station. The temperature data were available for mean daily temperature, daily minima and daily maxima.

Table 5.2 Summary of the four rainfall stations used for rainfall analyses and the calibration of the HBV model

Station	Elevation (meters above sea level)	Latitude (south)	Longitude (east)	Average annual rainfall (1981-2015)
Thyolo	820	16.13	35.13	1219.241 mm/year
Bvumbwe	1146	15.92	35.07	1159.459 mm/year
Mimosa	652	16.07	35.62	1606.67 mm/year
Makhanga	52			777.7117 mm/year

5.6.2 Runoff Data

The collection and management of discharge data from the available hydrometric stations is the mandate of the department of water resources management through the surface water resources section. The department maintains the HyData database from which daily discharge data for 7 hydrometric stations within the Ruo River basin were accessed, the most downstream of which was Ruo@Sinoya South. Daily discharge data from 1st January 1981 were made available with varying degrees of quality in terms of completeness and length of record, with the longest record being up to 2002 and the record for the most downstream hydrometric station on the Ruo River (Ruo@Sinoya South) extending only up to 1991. Flooding and vandalism have caused damage to a number of hydrometric stations in the Shire river basin posing a serious challenge to data availability such the quality of runoff data in general, has diminished for the past two decades or so. The key assumption with regards to this was therefore that the 10-year period was for which data was consistently available would be enough for the calibration and validation of the hydrological model.

5.6.3 Land Use Data

Land use data were obtained from the Malawi Spatial Data Portal (MASDAP), FAO Aquastat database and the European Space Association Database which provides a time series of land use since 1990. The data were specifically sought for the periods that represented the historical land use (1990) and one that represented the current land use and cover (2010). While land use encompasses quite a number of categories, the key categories of interest were land used for forestry and land under cultivation.

5.7 Calibration, Validation and Computation

In any modelling process, parameter sampling is a crucial process for the successful setting up and running of the model. In rainfall-runoff models such as this, that success is determined by how close to the observed run-off is the simulated run-off. The calibration can be automatic or manual. In automatic calibration, the modeller uses optimisation algorithms to sample the optimum combination of parameters that produce simulated discharge reasonably close to the observed discharge. Manual calibration involves visual inspection of the hydrograph volume and shape to observe how close to the observed run-off is the simulated run-off. The coefficient of efficiency (R^2) is also used to determine model efficiency i.e the closeness of simulate runoff to observed runoff. R^2 is given by the formula;

$$R^2 = \frac{\sum(\bar{Q}_o - Q_o)^2 - \sum(Q_c - Q_o)^2}{\sum(\bar{Q}_o - Q_o)^2};$$

where $\bar{Q}_o$ is the mean observed runoff, Q_o is the observed and Q_c is the simulated runoff. R^2 approaches 1 where the observation and simulation are in close agreement while 0 where they do not agree. Poor model performance and data can yield negative R^2 values. The recommendation for HBV model is to keep R^2 at greater than 0.81.

The HBV model version used in this study does not come with the package for the automatic calibration as such calibration was done manually. Each of the four subroutines has parameters controlling either the volume of the discharge or the shape of the hydrograph. The parameter sampling and adjustment process was done for both sets of parameters controlling these two aspects of the hydrograph. In the context of the HBV model, the parameters are classified as snow parameters, volume parameters, soil parameters, response parameters and damp parameters. The attention to the calibration process was in the following order; volume, soil, response and damp with no attention was paid to snow parameters given the fact that all precipitation in the basin is in form of rainfall. Table 5.2 shows the sampling range from which the parameter values were sampled highlighting the maximum and minimum values for the key parameters and the starting values (even though these are recommended for Scandinavian catchments but still provide a good starting point for the calibration process). The parameter values for each subbasin at that were used for the simulation.

Table 5.3 Parameter starting values and the range for sampling parameter values as recommended in the HBV model user guide

Parameter	**Starting value**	**Range**
Pcorr	1.0	
Pcalt	0.1	
Pcaltl	800	
Paclat up	0.0	
Tcalt	0.6	
Rfcf	1.0	0.8-1.3
Tt	0.0 (°C)	-2-2 (°C)
FC	Regional Specific	100-1500 (mm)
Lp	0.9	Less than or equal to 1
Beta	2.5	1-4
Cflux	0.5	0-2
Cevpfo	1.15	
K4	0.01	0.001-0.1 (unit day-1)
Perc	0.5	0.01-6 (mm day -1)
Khq	0.1	0.005-0.5 (unit day-1)
Hq	This parameter is calculated from the mean of the observation record and mean of the annual peaks in the record as will be described immediately after the table	
Alfa	0.6	0-1.5
Maxbaz	0.5	0-7
Covpl	1.1	
Anthorn	0.2	0.15-0.3
Stf	2	1 or 2

The parameters **lag** and **damp** did not change the hydrograph or the value of the coefficient of efficiency in which case the recommendation is to not use them. The parameter **hq** is calculated from the mean of the entire discharge observation record for the current basin and the mean of the annual peaks for that same basin from either of the following formulae;

$$hq=(MQ*MHQ)^{1/2} * 86.4 / (\text{Area of sub-basin in km}^2) \text{ or } hq=MHQ/2*86.6/(\text{Area of sub-basin in km}^2)$$

where *MQ* is the mean daily discharge for the entire record applicable to that catchment and *MHQ* is the mean of the annual peaks for that record. The parameter **hq** controls the volume and would have to be adjusted. Higher **hq** values produce higher volumes and vice versa. The second formula (i.e MHQ/2*86.6) was used as it produced volumes closer to the observation. The parameters ***icfi*** and ***icfo*** were very crucial in determining the model's sensitivity to changes in land use. The former represents interception storage in field zones while the latter is for interception over forested zones. The two parameters, icfi and icfo, were very crucial to this particular study given their role in influencing runoff characteristics based on the land use characterisation used for the simulation.

Given the incompleteness of the data, it was very difficult to realise a higher R^2 for longer simulations as such the calibration mainly relied on visual inspection of the hydrograph at the most downstream station (Ruo @ Sinoya South). Nonetheless, the value of R^2 was still checked for shorter periods for when data was consistently available as well as for the smaller sub-basins that had relatively longer observation periods. Observed and modelled daily discharge values were also compared for each subbasin where such data were available. Figure 5.3 is a comparison of the modelled and observed discharge at the most downstream station. Other than visual inspection of the hydrographs of modelled and observed discharge, statistics such as mean, median and maximum were also compared to ensure that the statistics for the modelled runoff were kept as close to the observed as possible. Data challenges still presented a very big challenge in achieving that and this can be highlighted as one of the biggest limitations for this study.

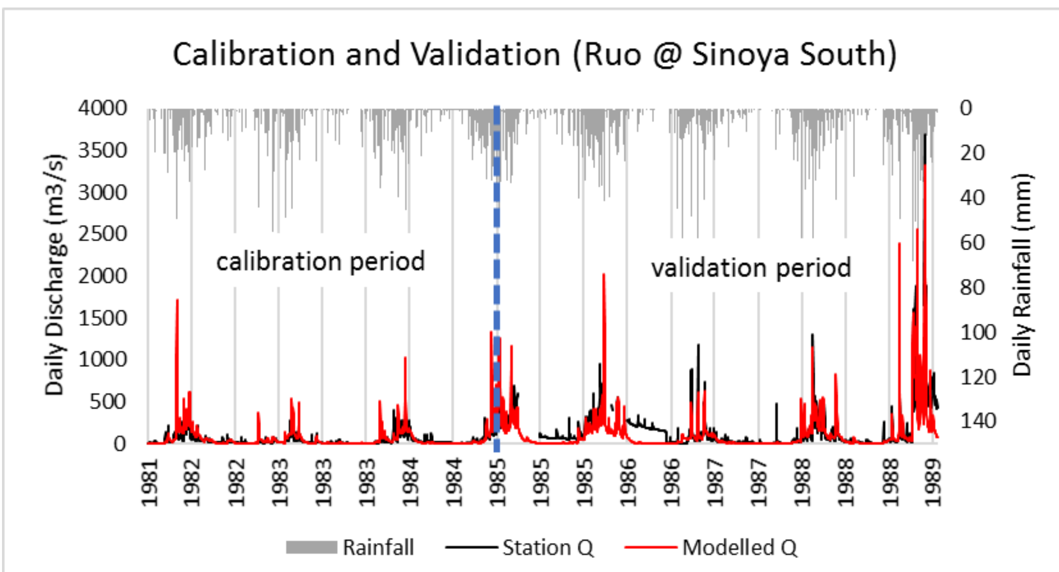


Figure 5.3 Modelled and observed runoff for Ruo River at the most downstream station

The challenges of working in ungauged catchments have been demonstrated in a number of hydrological assessment and this study was no exemption to these. In some cases, there are also spatial and temporal inconsistencies in station networks, where meteorological data may be available for one particular area for which there is no hydrological data available and vice versa. I this study, for instance, hydrological data was available in good quality and for long periods for the period between the 1960s and 1991 while the rainfall and temperature records was consistently available from 1981 to present. This prompted the choice of the period between 1981 and 1991 for the calibration and validation as indicated in figure 5.3.

The same parameters were used for the two different land use characterisations. To determine whether the model would pick any land use and land characterisation influences, comparisons were made between discharge generated based on simulations using observed rainfall datasets with different land use characterisation. Most aspects of the hydrograph and the pattern of discharge variable did not change given that parameters were not changed. However, there was a notable increase in the volume of daily, monthly and annual runoff volumes with an increase in the volume of these variables consistent with reduction in the area of land covered with forests. Figure 5.4 highlights the influence of land use on daily peak flows depicting how conversion of forest land to farmland may influence peak flows. Following "successful" calibration and validation, the model was run 800 times, 200 for each combination of climate and land use scenarios based on the 200 realisations for each climate scenario as highlighted in preceding sections. Thus, each one of the 400 climate realisations was used to run the model twice, with two different land use characterisations.

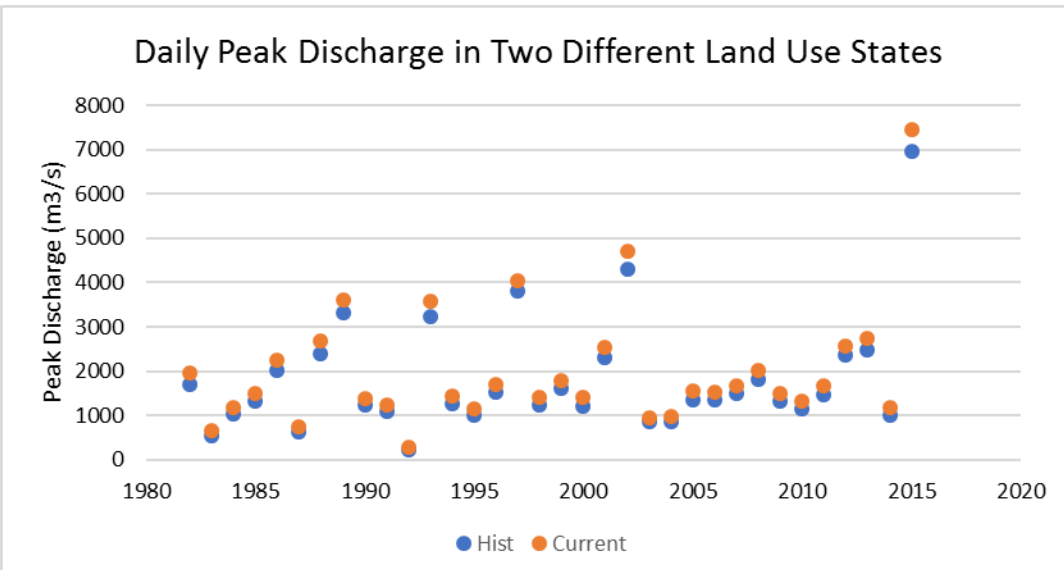


Figure 5.4 Daily peak discharge simulated in HBV with same set of parameters and observed data but different land characterisation highlighting the influence of replacing forests with farmland

5.8 Calculation of FAR

The fraction of attributable risk was calculated for each of the three metrics namely 1-Day, 10-Day and 30-Day maximum flows in order to determine the proportion of the risk of exceeding annual 1-day, 10-day and 30-peaks attributable to climate change (due to anthropogenic GHG emissions), land use and cover change as well as a combination of the two factors. The approach to evaluating the fraction of attributable risk links to the climate simulations and utilisation of climate attribution data to run the hydrological model given that results from all runs were analysed with no proviso that runs employed for the analysis only be those that had reproduced climate conditions close to those observed in January 2015 (i.e simulated tropical cyclones and or storms). The National Academies of Scinece Engineering and Medicine (2016) distinguish between conditioned and unconditioned attribution in greater detail. On one hand, conditioned attribution limits the analysis to a particular type of weather or climate situations. Such approaches often condition simulations and/or analyses based on imposed constraints such as SST anomalies or large-scale circulation patterns. While conditioning does improve the signal-noise ratio, it has been found that the probability distributions from conditional attribution experiments are narrower and forgo the stricter analysis of change in the probability in the state of interest in instances where the conditional state is absent (National Academies of Science Engineering and Medicine, 2016; Shepherd, 2016). On the other hand, unconditional attribution uses all simulations and results from such analyses are often thought as more comprehensive and most easily interpretable (National Academies of Science Engineering and Medicine, 2016). In the context of this study and given the shortcomings of the model to always realistically simulate tropical cyclones and depressions, an unconditional analysis was sought.

FARs for the 1-day maxima, 10-day maxima and 30-day maxima were determined for the three scenarios on the basis of how their exceedance probabilities for a pre-determined threshold related with the exceedance probability for the same value in the control scenario ("counter-factual" climate and historical land use combination). The thresholds used for the determination of the exceedance probabilities are based on maxima for daily, 10-day and 30-day events highlighted in table 4.1.

The analysis was constrained to high-flow periods from January to April. 120-day (Jan-Apr) streamflow outputs for each of the 200 runs per scenario (climate-land use combination) were aggregated into one record representing a 200-year record (i.e, the 200 simulations for each case were stacked together and treated as if they were 200 different years for which the analysis was performed). 1-day, 10-day, and 30-day maximum flows were determined for each run with the 10-day and 30-day maxima being determined from the running means at 10-day and 30-day intervals respectively. Generalised extreme value distribution parameters were determined for each of the three metrics based on L-Moments in each of the four sets of scenarios (control, and three test scenarios). The return periods for the thresholds for the 1-day, 10-day and 30-day maxima thresholds were determined with the exceedance probabilities for those thresholds determined based on the relationship; Probability $_{\text{exceedance}}$=1/Return Period. The uncertainty intervals for the probability distribution and return periods were determined by bootstrapping the distribution 1000 times at 0.95 confidence level. This would help explore how results were bound by sampling uncertainty. Given the four sets of hydrological simulations;

Control: "Counterfactual Climate and Historical Land Use"

Scenario A: "Factual Climate and Historical land use"

Scenario B: "Counterfactual climate and current land use"

Scenario C: "Factual climate and current land use"

three sets of FAR for a predetermined threshold were calculated for the 1-day, 10-day and 30-day maxima, based on the formula "FAR=1-($P_{control}$/$P_{scenariox}$)" for each of the three scenarios to determine;

- For Scenario A; the proportion of the risk of exceeding a specified 1-day peak, 10-day maximum, and 30-day maximum flows attributable to climate change from anthropogenic GHG emissions if land use had not changed
- For scenario B; the proportion of the risk of exceeding the threshold for the three metrics attributable to land use change if the climate had not changed due to anthropogenic GHG emissions

- For scenario C; the proportion of the risk of exceeding the threshold for the three metrics attributable to climate change from anthropogenic GHG emissions while minding the possible contribution of land use changes.

In some cases, a negative FAR would be realised which would imply that external factors (i.e climate change and land use and cover change) contribute to a decrease in the risk of exceeding a threshold. In such instances a FAR(d), denoting reduction in the risk, was calculated by flipping the probabilities in the FAR formula, as suggested and demonstrated by Wolski *et al.* (2014), such that the fraction of attributable risk reduction is $FAR(d)=1-(P_{scenario\ x}/P_{control})$ such that "$P_{scenario\ x}$" is the probability of exceeding a threshold of the metric in any of the three scenarios and "$P_{control}$" is the probability of exceeding the metrics in the control scenario.

6 Results and Discussion

This chapter presents the results for the change in risk of extreme flood events in the three scenarios of climate and land use and cover in relation to the control. Results include the return periods for peak flows at different durations in the three difference scenarios to the control, as well as how the return periods relate to the exceedance probabilities and ultimately the fraction of the risk of peak flows at different durations attributable to climate change, land use and cover change, as well as a combination of both. The chapter also highlights differences in two datasets-station and CHIRPS- based on selected rainfall indices and how such differences may affect attribution results. In a way, this highlights the observed data challenges typical of most areas within the region while underlining the need for proper assessment and interpolation of datasets before application in studies of this nature.

6.1.1 Change in Risk of 1-Day Maxima Events

The return period for the 2015 annual peak varied in the three different scenarios as illustrated in figure 6.1 The return period for a daily peak of 6950 m³/s was much higher in the "factual" (current) climate as compared to the "counterfactual" (historic) climate in a scenario where land use during the year of the event was the same as in the historical reference period. Consequently, the probability of exceeding that daily peak was much lower in the "factual" climate as compared to the "counterfactual" climate if the role of land use and cover change is unaccounted for. However, altering land use characteristics to resemble the land use characteristics at the time of the occurrence of the event, in a scenario where climate had not been influenced by anthropogenic greenhouse gas emissions, led to a decrease in the return period of the 6950 m³/s peak flow implying a positive contribution to the chance of exceeding such an extreme event. Considering a change in both factors (scenario C) highlighted that while there was a decrease in the probability of exceeding the 1-day maximum threshold in the "factual" climate, the decline was in itself masked or undermined by changes in land use and cover. The return intervals were bootstrapped 1000 times for each case and the confidence interval at 95% confidence level derived. The uncertainty is visualised in the corresponding plots for each scenario and confidence intervals for the return levels corresponding to a return period of the simulated runoff threshold for Q2015 presented in the tables of results. Previous studies evaluating uncertainty through bootstrapping or resampling approached have demonstrated that short record lengths (in this case simulations) are associated with considerable uncertainty in the estimates of event thresholds or quartiles with long return period (Burn, 2003). Nonetheless the consistency in the differences between exceedance probabilities do indicate a stable relationship between the exceedance probabilities in different sample distributions.

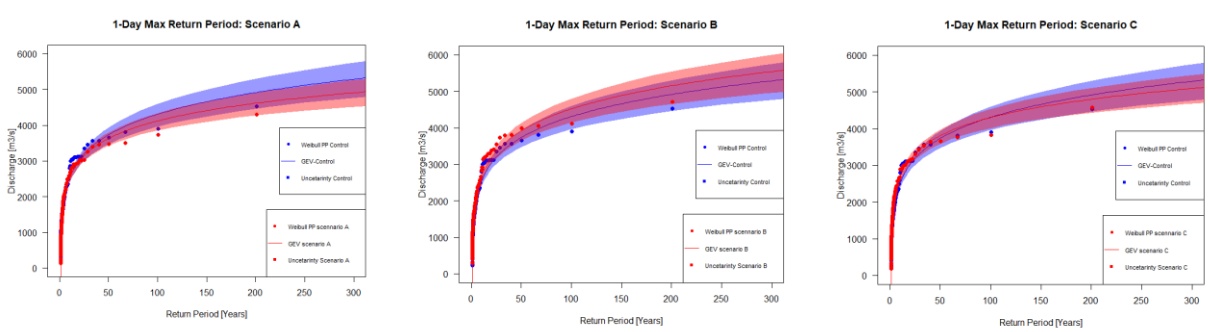


Figure 6.1 1-Day Maximum return periods in the three experimental scenarios highlighting the role of climate change (a), land use change (b) and the joint influence by both risk factors (c), Weibull PP indicates the Weibull plotting positions for the distribution

The return periods, exceedance probabilities and FARs for each case are presented in table 6.1which clearly indicates that the probability of exceeding the threshold was low in both the "factual" and "counter-factual" climates, nonetheless higher in the "counterfactual" climate. The negative fraction of attributable risk for the both cases of "factual" climate indicates a reduction in the likelihood of experiencing an event of the threshold's magnitude in the "factual" climate. However, the decrease in the likelihood is lower when the role of land use and cover change on influencing the risk is accounted for. The role of land use change alone is highlighted in scenario B where, the risk of flooding increases as land use changes but climate remains the same. Negative fraction of attributable risk in the "factual" climate scenario is an indication that there is a reduction in the chance of high-risk discharge attributed to climate change from anthropogenic greenhouse gas emissions.

Table 6.1 Return period, exceedance probability and fraction of risk attributable to climate change, land use change, and a combination of both for 1-Day Max

Scenario	Threshold (M^3/S)	Return Period (Years)	Confidence Interval for return periods at α=0.05 (M^3/S)	Exceedance Probability	FAR	FAR(d)
Control	6950	1558.70	4807.05, 10073.30	0.00064		
A (climate change only)	6950	4585.10	4976.66, 10021.82	0.00022	-1.94	0.66
B (land use changes only)	6950	1155.50	4993.87, 9833.67	0.00087	0.27	
C (both climate and land use change)	6950	3661.80	4968.78, 10090.41	0.00027	-1.35	0.57

6.1.2 Change in Risk of 10-Day Maxima Events

Changes in the return period of 10-day maxima were consistent across the three different scenarios as, in each scenario, there was an increase in the return period of 10-day maxima (2233 c^3/s) events in relation to the control. There was an increase in the return period of the threshold event in both in scenarios where only climate or land use were changed, each to closely resemble the climate and land use characteristics at the time of event. Changes in climate led to a much higher increase in the exceedance probability of that threshold as compared to land use and cover change. The return period was even lower, hence the exceedance probability higher, when both factors were considered in scenario C which evaluates the change in the return period of the event when both land use and climate change. As opposed to the 1-day maxima, where the probability of exceeding the threshold flow decreases in the "factual" climate, the exceedance probability of the 10-day max threshold increases in the "factual" climate. Land use however plays the same role in modifying the exceedance probability and the risk with a positive contribution which increases the extent of the increase in likelihood of experiencing extreme 10-day max events and reduces the extent of the decrease in likelihood of experiencing extreme 1-day events in the current climate.

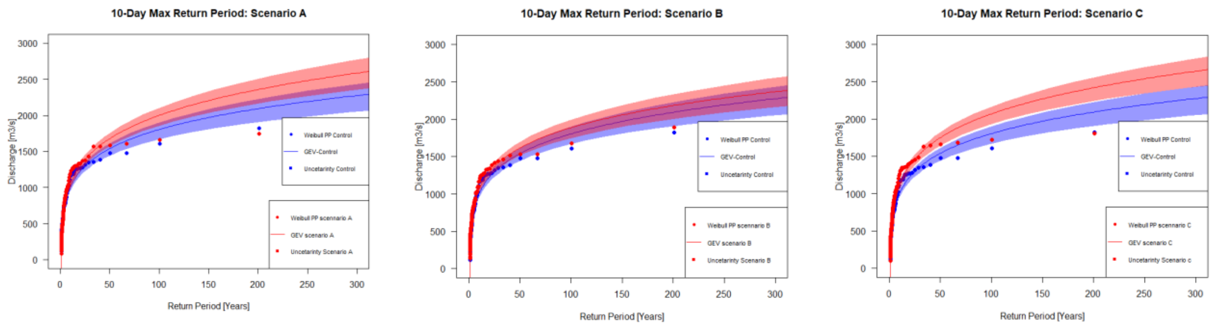


Figure 6.2 10-Day Maximum return periods in the three experimental scenarios highlighting the role of climate change (a), land use change (b) and the joint influence by both risk factors (c)

10 consecutive days with an average daily flow of 2233 m^3/s have the lowest return period, hence the highest probability of being exceeded, in scenario C where both climate and land use and cover are changed. The relative contribution to the risk by climate change and land use and cover change is highlighted in scenarios A and B respectively. In this case, both factors lead to an increase in the likelihood of experiencing an event of such magnitude but the increase is much higher when only climate change is considered as compared to when only land use change is considered. Notable in this relationship are the differences in the direction of influence that climate change has on the 1-Day max and 10-day max as well as the difference in the extent of the relative contribution between climate change and land use and cover change in the two metrics, i.e. 1-day max and 10-day max. This could be attributed to a combination of both meteorological and hydrological factors resulting from changes in the distribution of the consecutive days with high amounts of rainfall as well as changes in antecedent conditions that may influence runoff over a number of consecutive days. Such relationships might also indicate the relative importance of rainfall persistence, rather than absolute daily volumes, in influencing flood extremity.

Table 6.2 Return period, exceedance probability and fraction of risk attributable to climate change, land use change, and a combination of both for 10-day max

Scenario	Threshold (M^3/S)	Return Period (Years)	Confidence Interval for return periods at α=0.05 (M^3/S)	Exceedance Probability	FAR
Control	2233	274.7	1692.07, 2993.93	0.0036	
A (climate change only)	2233	158.5	1727.15, 2903.60	0.0063	0.42
B (land use change only)	2233	224.2	1724.39, 2914.47	0.0045	0.18
C (both climate and land use change)	2233	139.8	1733.25, 2919.54	0.0072	0.49

6.1.3 Change in Risk of 30-Day Maxima Events

The changes in exceedance probability for the 30-day maxima were also consistently positive in each of the three scenarios against the control. As illustrated in figure 6.3 and summarised in table 6.3, there is a decrease in the return period of 30 consecutive days with an average daily flow of 1226 m^3/s for scenarios A and B, and a much lower return period of such events in scenario C, underlining the positive influence that both climate change and land use and cover change has on discharge.

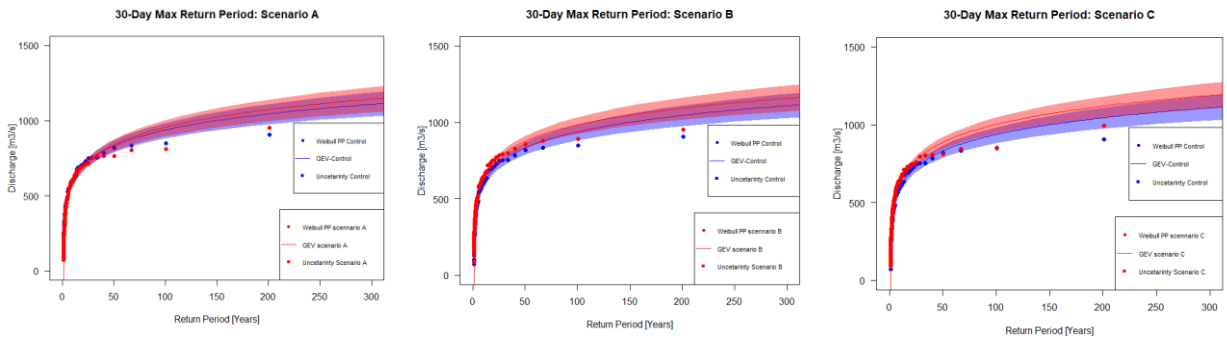


Figure 6.3 30-Day Maximum return periods in the three experimental scenarios highlighting the role of climate change (a), land use change (b) and the joint influence by both risk factors (c)

The probability of exceeding 30-consecuitive days with an average flow of 1226 m³/s is higher in each case where only land use or climate is changed. This is summarised in table 5.4 which indicates that 23% of that risk is attributable to climate change if land use stays the same while 26% of the risk is attributable to land use and cover change if climate stays the same i.e. if there was no human influence through greenhouse gas emissions. The risk attributable to external factors is much higher when both climate change and land use and cover are changed resulting in a lower return period for an event of that magnitude.

Table 6.3 Return period, exceedance probability and fraction of risk attributable to climate change, land use change, and a combination of both for 30-Day Max

Scenario	Threshold (M³/S)	Return Period (Years)	Confidence Interval for return periods at α=0.05 (M³/S)	Exceedance Probability	FAR
Control (historical land use and counterfactual climate)	1226	624.2	962.19, 1621.65	0.0016	
A (historical land use vs factual climate)	1226	478.6	971.82, 1586.28	0.0021	0.23
B (current land use vs counterfactual climate)	1226	459.1	973.79, 1569.07	0.0022	0.26
C (factual climate and current land use)	1226	372.1	988.50, 1565.13	0.0027	0.40

6.1.4 General Interpretation of Changes in Flood Risk

Despite the differences in the direction of the change in exceedance probability, hence FAR, between the 1-Day maxima and the other two metrics in the "factual" climates, it was generally established that land use and cover change consistently increased the likelihood of occurrence for a Q2015 extreme event. The modulation of the likelihood by land use and cover change meant that for the 1-day maxima, whose likelihood reduced in the "factual" climate, the extent of the decrease in the exceedance probability was to an extent masked by land use change. This is evident from the case where both land use and climate change are altered to represent present day where the decrease in likelihood of an extreme event of Q2015 magnitude was less apparent as compare to when only a change in climate was considered in scenario A. An alternative expression of this relationship is that climate change reduced the extent of the increase in the likelihood of flooding as attributable to land use and cover change. Furthermore, the extent of the increase in the likelihood of exceeding the 10-day and 30-day maxima thresholds in the simulated factual climate was found to be even higher when the influence of changes in land use and cover were accounted for.

Two things were generally apparent from the results; 1) while the influence on the direction of change of the risk attributable to climate change was dependent on metric, the influence on the direction of change of the risk attributable to land use and cover change was consistently towards an increase in the risk; 2) the change in the likelihood of exceeding the threshold of any metric (1-day max, 10-day max, 30-day max) as a result of climate change and land use and cover change (scenario C) was a sum of the proportion of the risk attributable to climate change and the proportion of the risk attributable to land use change. Figure 6.4 illustrates how the likelihood of flooding when the two external factors are considered is a sum of the two when they are considered separately. This however is not a direct arithmetic sum due to the interaction of meteorological and hydrological factors when both land use and climate are changed highlighting that the result of the influence of both factors, though cumulative, is not a direct arithmetic sum of the two.

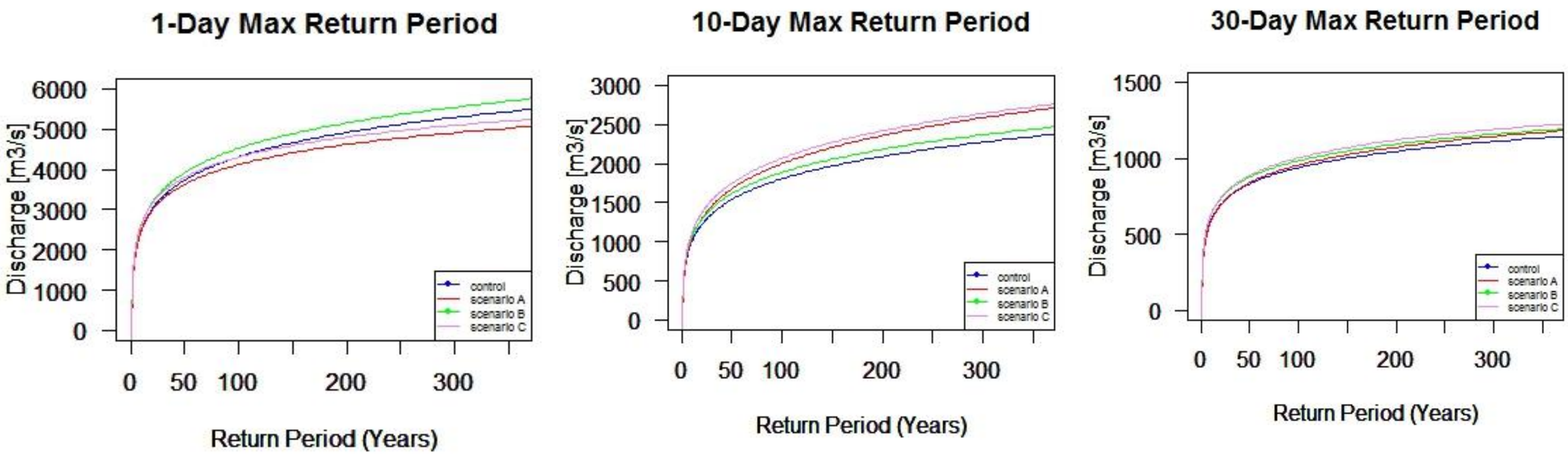


Figure 6.4 Relationship of the change in risk in the three scenarios highlight the consistent "sum" effect of the two risk factors

Studies analysing the risk of flooding as a result of changes in climate and land use have previously demonstrated that the risk of floods may change as a result of changes in both factors with the direction of change being the result of the interaction between the two factors. For instance, Emam *et al.* (2016) found in the context of Indonesia, that both climate and land use changes would increase the risk of future climate. Studying in the context of the Upper Ciliwung River, Emam *et al.* (2016) established that changes in rainfall characteristics such as intensity, and the increase in amount of rainfall received on consecutive days, positively contribute to runoff as does rapid urbanisation and changes in catchment characteristics that reduce infiltration. Guo, Hu and Jiang (2008), also highlighted the role that land use change plays in moderating the risk of flooding in Poyang Lake basin in China where they established that the risk of flooding increased with reduced land cover. Guo, Hu and Jiang's (2008) assessment of the influence of climate was however based on observations as such comparisons to this study based on climate parameters from climate models may not be entirely valid.

A notable case of joint risk assessment was also presented by Yengoh, Fogwe and Armah (2017) who, in the context of the Cameroonian metropolis of Doula, found that the risk of flooding had increased as a result of changes in land use and that climate change did not have a role to play. While studying in the Ngerengere River catchment in Tanzania, Natkhin *et al.* (2015), established that climate change and land use change had different influences on high flow events such that climate change actually reduced the severity of floods while land use change worked in the opposite direction. This is particularly consistent with what was established in this study with regards to the 1-day duration events. Elsewhere in Malawi, Palamuleni, Ndomba and Annegarn (2011) found that land use change had an impact on hydrological regimes in the upper Shire River basin. Their study demonstrated that surface and ground water declines while runoff increases as the land use changes from forests to rural built-up areas and subsistence agriculture. The model used for this study however only allowed for two possible land use change; forest and field in which case land use change was simply based on changing the amount of land area under forest cover and under agriculture. The main difference arises from the differences in evaporation and interception storage which, for the latter, is controlled by two different parameters for forest and field. Where possible and feasible, a more comprehensive land use characterisation would be ideal.

This study also highlighted the possibility that risk analysis and conclusions of how the risk changes with changes in external factors is to an extent bound by the metrics used to analyse the risk. Kay *et al.* (2011) showed, in the context of the UK autumn/winter 2000 flood risk attribution, that FAR results and distribution can differ based on the metric. In a study that was based on 1-day, 10-day and 30-day maxima and done in a more than one catchment, Kay *et al.* (2011) established that the distribution of the FAR would change with duration. For longer term durations, the variation was generally attributed to a combination of factors such as catchment response time, seasonal changes in rainfall and balance with evapotranspiration and temporal distribution of rainfall while the variation in 1-day durations were generally based on catchment response based on permeability and the role of ground water as well as difference in daily rainfall intensities. Understanding such physical processes should therefore form an essential part of attribution studies, more so where such studies analyses differences between catchment. The importance of metrics for climate change impacts on hydrological systems has been further highlighted by Ekström *et al.* (2018).

A key revelation from this study is the possibility to condition hydrological modelling experiments for attribution to be able to account for the influence of climate change while quantitatively accounting for the contribution to risk by other external factors-land use and cover change in this case. Stott *et al.* (2016) note that potential challenges may arise when attribution is to be considered as multifactorial and highlight the need for accounting for other external risk factors (such as land use changes) so that attribution is not solely a climatic enquiry but rather an assessment of the risk posed by climate change against the background of other changing, and perhaps equally important, risk factors. Accounting for other factors also add confidence to the attribution it is often the case that confidence in attribution is high when the event under consideration is purely from meteorological influence or when other confounding factors such as land use and management are carefully and reliably considered.

Findings in this study also do have implications for policy with regards to disaster risk reduction and management. The government of Malawi and its development have for long recognised the need for catchment management and land restoration to reduce the risk of flooding. Global risk factors through climate change have been highlighted as shown by the contribution to the risk of flooding by climate change from anthropogenic emissions of greenhouse gases. Mitigation is one way to reduce the risk of flooding as a result of change in the meteorological aspects i.e. rainfall and temperature, on one hand. On the other hand, proper land management through efforts to curb deforestation and restore degraded land is one way of adapting to the increase in risk of extreme flood events. Understanding the relative contribution of the two external factors offers an opportunity informed catchment management and land restoration appraisals as a means for flood risk mitigation. Other than that, joint attribution or risk disaggregation offers a more robust approach to loss and damage assessments as the is an opportunity to isolate the contribution to the risk by other external, a thing which attribution scholars have often highlighted as a challenge in basing claims of damage merely on climate change from anthropogenic greenhouse gas emissions.

6.2 Typical Observation Limitations and Confidence in Risk-Based Event Attribution Studies

Confidence in attribution of extreme events to climate is also bound, to some extent, by observation data-both quality and quantity. The challenges in observation over this region have been well documented and they are a well-known challenge in climate science studies as well as other applications (Jones et al., 2015; Vincent, Dougill, Dixon, Stringer, & Cull, 2017; Vincent, Dougill, Mkwambisi, Cull, & Stringer, 2014). Alternatives to station data exist including satellite and reanalysis datasets. However, some of such alternatives, a bulk of which are satellite-based observation datasets have been known to have limitations in usability for certain purposes over some regions generally due to issues of resolution and topography for instance, leading to high observational uncertainties and to an extent limiting the usability of such products for some applications. In this study, station data was used with CHIRPS data available as an alternative to the same. Section 4.3 dwelled on the characterisation of rainfall during the 2014/15 season in the context of the climatology of the basin and it was seen, at least from the characterisation of the seasonal anomalies, that different datasets may have different representations of rainfall variables and the extent of the differences may have an influence on results and conclusions from studies of this nature. Apart from misleading event characterisation, such differences may be projected on to the model evaluation and downscaling processes as well as the calibration and validation of the hydrological models and, potentially, lead to significant uncertainties. Moreover, this study generally relied on the rainfall data to generate streamflow data for the periods where such streamflow data were not available as such the reliability of streamflow data (generated from running the model with observed rainfall data) is not only as good as the model set up but the rainfall data with which the model is run too. This analysis specifically focused on the distribution of annual and seasonal rainfall as well shorter temporal scale monthly and daily maxima with the latter reflecting on the representation of extreme events too. The distributions of the wet day frequency were also analysed.

6.2.1 Differences in Extreme Rainfall Frequencies between Datasets

The data challenges with observed rainfall and other meteorological variables has been well documented. This region is generally characterised with data availability challenges in terms of the spatial and temporal scale for which data are available. Station and CHIRPS datasets were analysed and compared for indices relating to extreme events and potentially severe rainfall events. Potential severity of the rainfall is defined in this case as rainfall events most likely to lead to extreme runoff flooding. The threshold for highly extreme rainfall was set at 50mm/day rain. Figure 6.5 is 4-station sum of event above 50mm/day and indicates that the CHIRPS dataset underestimates high extremes as such it may not be ideal for extreme rainfall-runoff studies, especially for this region.

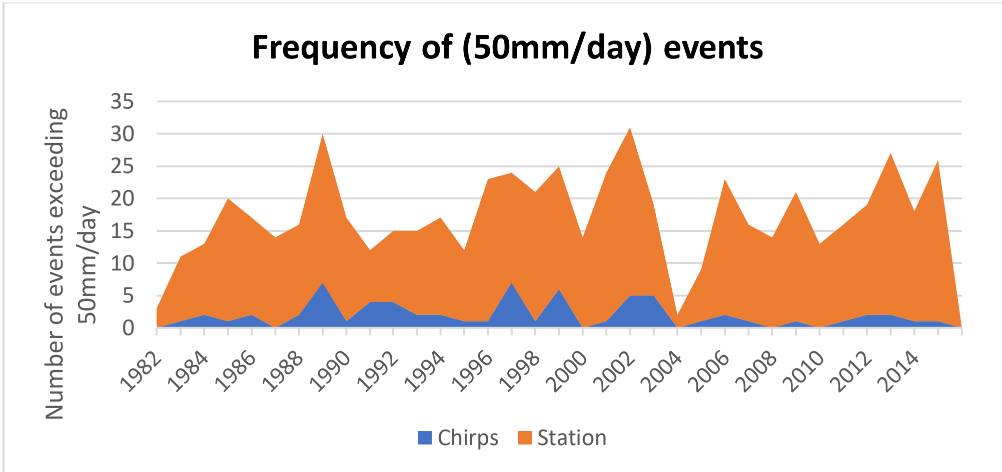


Figure 6.5 Number of days with rainfall above 50mm in Station and CHIRPS datasets indicating an underrepresentation of such events in CHIRPS dataset for this region and most importantly for the 2014/15 season

6.2.2 Comparison of Rainfall Parameter Distribution

Box and whisker plots for the four stations and their corresponding points in the CHIRPS data were plotted to determine the differences in the distribution of various variables in the two databases. In statistical analyses, the box-and-whisker plot is used to describe the distribution of the two datasets using a five-number summary (mean, median, minimum, maximum, as well as 25th and 75th percentiles). This analysis was done for the annual rainfall for the entire series as well as for the seasonal, monthly and daily maxima. The annual and seasonal rainfall would give an indication of how the differences in the two datasets in general terms. The monthly rainfall distribution would give an indication of whether the datasets differ when shorter temporal scales are considered. Daily rainfall was not considered given the high variability on a daily scale. However, daily maxima were analysed on the basis of the distribution of maximum rainfall as a proxy for how the datasets capture extreme rainfall. This analysis would complement the analysis of the frequency of >50mm/day rainfall to depict how the two datasets vary in terms of extreme events.

Figure 6.6 (a-d) summarises the distribution of rainfall metrics namely annual, seasonal, monthly and daily maxima for the four stations in the two datasets. The 5-number summaries highlight the differences between the two datasets with the CHIRPS datasets consistently underestimating these metrics. Issues with systematic biases and errors in satellite rainfall datasets have been highlighted before by Dinku *et al.* (2007) as well as Wolski *et al.* (2012) who noted the limited usability of such products for downscaling GCM outputs in some regions. In particular, Dinku *et al.* (2007) highlights how the usability of satellite data could be limited in areas with complex topography such as the one under study in this case given the important role that the Mount Mulanje plays in controlling rainfall in the basin. However, this is not conclusive for this case and a more comprehensive assessment may be required.

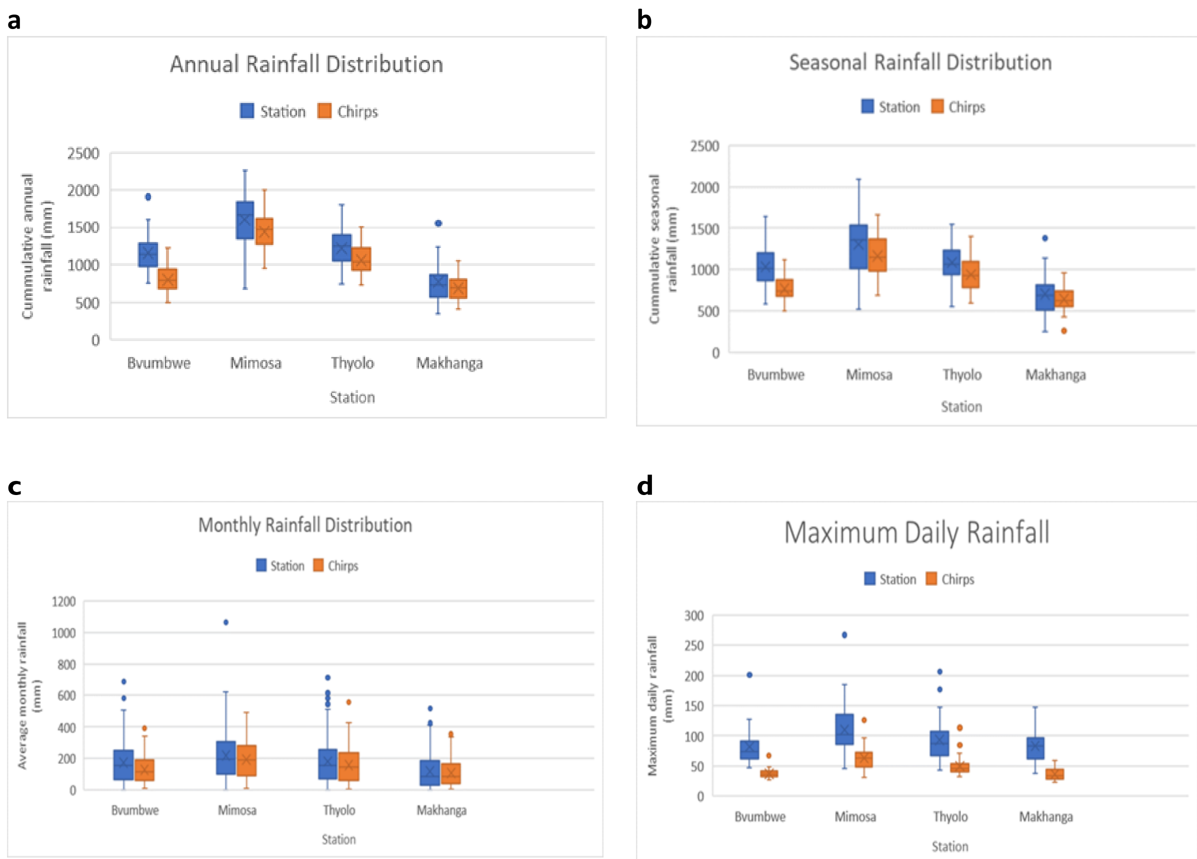


Figure 6.6 Distribution of rainfall indices in the two observational datasets for annual rainfall (a), seasonal rainfall (b), monthly rainfall (c) and daily maxima (d)

The differences in the volume of rainfall could potentially arise from the differences in number of wet days and/or the volume of rainfall per day. The analyses reported have so far indicated that the CHIRPS data generally underestimates daily volumes more so for intense daily events as shown in figure 6.6d. This is further coupled with an underestimation of the number of wet days in a season as illustrated in figure 6.7. Significant differences in the observation datasets highlights the observation uncertainties that may limit studies of this nature. It is already known that regions such as these have data challenges which could diminish the confidence in event attribution. Such limitations are experienced in terms of both efforts to downscale GCM outputs on the basis of various observation datasets as well as in the characterisation of the extreme events. For the latter, one would run the risk of under or overestimating the thresholds from which to determine the exceedance probabilities and ultimately the FAR. More so for this study given that the threshold for the flood events was derived from the observed rainfall data as a result of further challenges in runoff data availability. This highlights the need to invest in data both in terms of research as well as infrastructure and personnel to aid the collection and management of such data to instil more confidence in findings from studies of this nature.

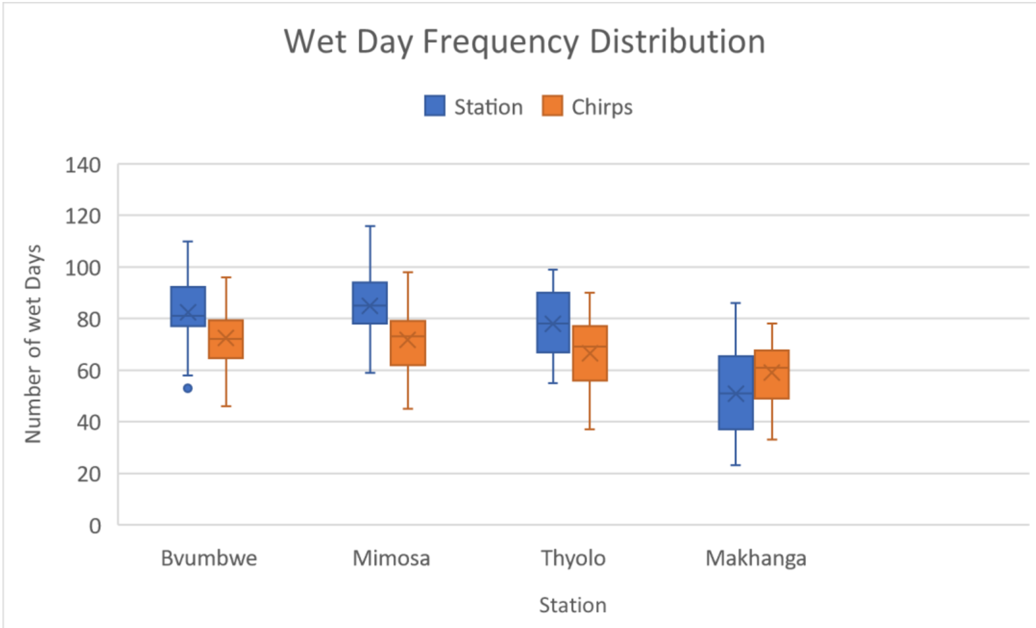


Figure 6.7 Wet day frequency distribution in station and CHIRPS datasets indicating an underestimation of number of wet days in CHIRPS consistent across three stations

The distribution of the different indices in the station and CHIRPS data indicates, to an extent, the role that observational challenges may have on event attribution studies. Such challenges could be experienced during the downscaling process, calibration and validation of the hydrological model, as well as the characterisation of the extreme event. In this study, these three processes critically relied on observed data as such it was essential that such data be as robust and credible to avoid inaccurate simulation of the runoff as well as characterisation of the event which would in turn influence the value of the FAR. Specific to this study, the characterisation of the extreme event in the absence of observed runoff generally relied on the observed rainfall data as such data of poor quality would have led to a misrepresentation of the extreme event. More comprehensive analyses of observation uncertainties have been done and often use more than two datasets for example Sylla *et al.* (2013), Dinku *et al.* (2007). The scope of this study however, limited the analysis to two datasets with the choice of the CHIRPS data based on the extent to which that data has been used in recent projects. A more comprehensive analysis could be done to fully analyse the role of observational uncertainties in attribution studies.

6.3 Other Limitations and Sources of Uncertainty

For confidence, attribution studies often use an ensemble of GCMs so that conclusions are not limited to the ability or inability of the climate model to actually represent the observed climate. By evaluating the differences in results from different GCM outputs, one is also in a position to evaluate the extent to which results are actually influenced by climate model and build stronger confidence in the results and conclusions. This study only used one GCM as such the results may have only been as good as this particular model's ability to actually represent the observed climate. Other than that, the downscaling procedure also contributes to the uncertainty of the results. Specifically, there are likely uncertainties in terms of representation of extreme daily rainfall as the downscale procedure is generally based on observed ECDF, and thus limited to conditions that have actually been observed and potentially constraining the range of variability to downscaled rainfall. Furthermore, some the representation of land use and land cover within the HBV model and the fact that land use and land cover comparisons are based on post 1990 changes presents a particular set of uncertainty. The assumption in that case that the land use and land cover in 1990 was representative of the land use and land cover in pre-industrial times (consistent with the "counter-factual" climate) yet there may be differences over that period of time. Finally, uncertainty could potentially arise from the definition of the event and the fact that there were no precise hydrological data as well as specified timing and location of the flood. That, coupled with the size of the catchment being analysed, means that it is difficult to identify the temporal scale of the event. One way to counter this was the use of different time-based metrics i.e. 1-day, 10-day and 30-day maxima.

7 Summary, Conclusions and Recommendations

This study demonstrated the ability of the HBV model to simulate different scenarios of catchment land use and climate characteristics. The HBV model was set up to represent the Ruo River basin and, after calibration and validation, 800 simulations of rainfall-runoff relationships were done based on four scenarios - each scenario being a combination of land use and climate characteristics for the year 2015. The climatic characteristics were based on two simulated climate states. The "factual" state which was generated with atmospheric and SST conditions closely resembling those at the time of occurrence of the event, represented a climate state altered due to human interferences i.e the current climate. On the other hand, the "counterfactual" state was based on GCM simulations from natural forcings only, with the SST modified by subtracting the warming attributable to anthropogenic climate change, to simulate the climate as it would have been without human interferences through greenhouse gas emissions. Each climatic state was simulated 20 times-thus 40 in total-each time altering the initial conditions. The rainfall outputs for each run were downscaled 10 times using stochastic empirical downscaling procedure based on rainfall data from five stations within the Ruo Basin, thus creating 200 rainfall time series representing a particular climate (i.e. 200 time series for "factual" climate and 200 time series for "counter-factual" climate). Each time series was used to simulate runoff in the HBV model, with each run replicated once with altered land use and land cover. The land use and land cover characterisation were based on two states of land use, one based on vegetation characteristics in 1990 and the other based on vegetation characteristics in 2015 in the basin.

Based on the model's ability and the experimental set up of both the climate simulations as well as the rainfall-runoff simulations, the study attempted to answer questions around the extent to which climate change might have contributed to the 2015 flood event given the land use change in the basin which might have possibly contributed to the risk of flooding too.

The exceedance probability, as per first research question, of a flood of the Q2015 magnitude was found to be metric dependent and, for each metric, varied under different land use scenarios. The likelihood of exceeding a daily peak flow was found to be lower in the simulated factual climate as compared to the simulated counterfactual climate. However, extreme events of longer duration (10-days and 30-days) were more likely in the simulated factual climate as compared to the simulated counterfactual.

In each case, however, converting forested land into agricultural land heighted the likelihood of extreme discharge volumes such that even the reduction of the risk of extreme 1-day events in the current climate was to an extent masked by changes in land use. The contribution to the risk of flooding by land use and cover change was consistent for all three metrics. This was evident from the consistent positive change in the exceedance probabilities and corresponding fraction of attributable risk for the land use change only experiment. Noteworthy, however, the spread or sampling uncertainty of the distribution for the land use change only experiment was relatively consistently higher for all three metrics which could be attributed to both modelling uncertainties as well as the nature of hydrological responses to land use changes.

Regardless of the duration of the event, the likelihood of exceeding and extreme event of the Q2015 magnitude in the scenario where both climate and land use changed was a result of accumulation of the proportion of the risk by each of the two factors. Where climate change led to the reduction in the likelihood of exceeding an event of this nature, land use change limited the extent of the reduction. Land use change thus amplified the increase in the likelihood of flooding due to climate change (where the change was positive) and dampened the risk in the likelihood a Q2015 flood where the contribution to that from climate change was negative.

The final question would explore uncertainties in observed rainfall data and possible consequences and limitations which these may have on extreme event studies in general, and event attribution studies in particular. The study was done in a region where data are generally sparse, records short and sometimes incomplete, and these findings highlight the need to explore as many datasets as possible so that results from event attribution studies of this nature, as well as any other related fields of climate science, are robust and credible. The study has also acknowledged some of the sources of uncertainties that may limit confidence in results such that considerations can be made for future research to evaluate and reduce such uncertainties while taking care in using conclusions from this study for development application and other generalisations.

From the results of the current study and based on the duration of the extreme flood event of January 2015, it is likely that both climate change and changes in land use and cover may have contributed to the risk of experiencing floods of such a magnitude. However, the conclusiveness of the results, more so in terms of the relative contribution of each risk factor is to an extent bound by model and observation limitations. The relative risk attributable to each of the two risk factors is dependent on the duration for which the analysis is made with climate change having a relatively higher attributable risk for a 10-day event while there was no apparent in the difference in the attributable risk for 30-day events. The methodology used in this study also established the possibility of isolating the contribution by other risk factors to the risk of extreme events attributable to climate change. Attribution scholars, tracing back to Allen (2003) have often conceded the difficulty of concluding of attributing extreme evets such as floods to climate change given the contribution to the risk by other risk factors such as land use change. The ability to reliably account for other external risk factors therefore has the potential to improve the confidence in attribution studies and application of the same in a number of fields inter alia loss and damage assessments, tax claims, disaster risk management. Note has to be taken however that the findings from this study may not be widely applicable as results may depend on models used, experimental set up, and, as it is well-known, basic scale processes differ from one basin to another depending on basin characteristics.

7.1 Recommendations

Disaster risk reduction and management has become a key component of building resilience to climate change. However, efforts to reduce and manage risks of events that are not only dependent on climate change need to be well informed by comprehensive risk analyses that look at other risk factors and, where possible, quantitively account for the risk posed by climate change and other risk factors such as land use change. The FAR methodology presents an opportunity quantify the risk attributable to climate change thus being able to properly place efforts and investments that are informedly enough to address quantifiable risk factors. While there may be investments in engineering solutions to the risk of flooding, it should also be in the best interest to understand how restoration of ecosystems such as forest may provide alternative and reduce the risk of flooding, most importantly when the risk attributable to climate change is relatively lower than the risk attributable to land use change.

Investments in agriculture must also consider the implication that land use change as such considerable efforts should be made to ensure that forests are not degraded. Replacing forests with arable crops may have a different impact on flood risk as compared to replacing crops with perennial crops as such, where feasible, assessments and recommendations of land use change need to consider evaluating flood risk posed by different crops and only recommending those that have lowest contribution to flood risk from land use change.

Given the recent wave of extreme events, and the casual attribution of the same to climate change, it is paramount that more event attribution studies be done not only to get a perspective of what the future might look like in terms of weather-related extreme events, but to put in place measure to communities and investments are safeguarded from the risk of extreme events. Where feasibility permits, most certainly in impact assessments rather than attribution of purely meteorological events, efforts must be made to consider environmental change in its entirety to identify more opportunities for addressing the risk of extreme events. Furthermore, extreme event attribution forms a key part of loss and damage assessment and where possible joint attribution of impacts could be used as one way of enhancing the attribution of extreme events and associated loss and damage to climate change.

It is also known that assessments of climate change impacts are generally dependent on the ability of the models (both climate and impact) to ably simulate the processes of interest. While the ensemble approach is one way to handle the model inadequacies, this study only used only one model hence the results may only be as credible as the model's ability to simulate the climate of the region. The framework used for the climate modelling is based on an approach to enhance the simulatability of extreme events, however, without other models to compare with, the results may still be bound by the model's ability and therefore results constrained by model associated errors. Future studies should therefore explore the opportunity for using different models as well as model set ups.

A number of assessments of observation data and associated challenges in climate studies have been done and often recommended an improvement in the observational systems for both meteorological and hydrological data. Recent efforts by government and its development partners to improve meteorological and hydrological monitoring will improve not only understanding development applications for such information but observational data reliability for studies such as this.

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